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Collected Notes for NASA Workshop on the Automation of Time Series

(NASA Ames, May 12, 1993)

Coordinated by

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Ames Research Center

Artificial Intelligence Research Branch

Technical Report FIA-93-15

June, 1993

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1 The organization of this workshop and the preparation of this report was supported by NASA code FI (Information Sciences Division).

Contents

NASA Workshop on the Automation of Time Series, Signatures, and Trend Analysis

May 12, 1993

Philip Laird and Robert Shelton, Coordinators

This workshop was conceived as an outgrowth of a project to automate the monitoring of signatures acquired from shuttle telemetry. During preliminary discussions held in December 92, it became clear that even for the task at hand—a scientifically straight forward pattern recognition problem—there were a relatively large number of techniques which had been considered and/or used for similar projects within NASA, defense, and the private sector. The related issues of trend analysis and time series prediction arose from the discussion related to the application of certain advanced techniques from machine learning to the signature recognition problem. In spite of the diversity of the problem domain and proposed solutions, certain themes emerged. The common issues were data reduction, data management, feature extraction, and, perhaps most important, integration of advanced software architectures with data sources and end-users. Due to the criticality of this last issue of two-sided integration, when the decision to have the workshop was made, it was decided that unlike many purely technical and/or scientific conferences, the organizers would aggressively recruit participation from the operations community. The final program reflects a diversity of applications ranging from processing astronomical observations to tracking of problem reports. The talks included frontier technical areas such as wavelets, neural networks and artificial intelligence, as well as user interfaces, data management, and foremost, needs of our customers. Participants were drawn from eight NASA centers with an invited talk given by Professor Andreas Weigend of the Department of Computer Science at the University of Colorado, Boulder. A three hour segment of the conference included a live video link among six NASA centers for which facilities were available.

Robert Shelton,
Co-coordinator

Speakers and Coordinators for the
NASA Workshop on the Automation of Time Series,
Signatures, and Trend Analysis

May 12, 1993

Morning Session
Building N213, Room 261
NASA Ames Research Center

Robert Shelton, Chair
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Mail Code PT41
Houston, TX 77058
713-483-5901
SHELTON@GOTHAMCITY.JSC.NASA.GOV

8:30 -- 9:00
A Health Monitoring Expert System
June Zakrajsek
NASA Lewis Research Center
21000 Brookpark Rd.
Cleveland, OH 44135
216-433-7470
JUNE@ENGLAND.LERC.NASA.GOV

9:00 -- 9:30
A Pattern Recognition Toolkit for Analyzing Signatures in Shuttle Telemetry Data
Dave Hammen
Mitre Corp.
1120 NASA Rd. 1
Houston, TX 77058
713-335-8510
DHAMMEN@MITRE.ORG

9:30 -- 10:00
Analysis of Stochastic Time Series Data
Jeff Scargle
NASA Ames Research Center
Mail Stop 245-3
Moffett Field, CA 94035-1000
415-604-6330
JEFFREY@SUNSHINE.ARC.NASA.GOV

10:15 -- 10:45
Comparison of Temporal Analysis Methods
Jay Norris
Code 668
NASA Goddard Space Flight Center /LHEA/GROSSC

Greenbelt, MD 20771
301-286-3367
NORRIS@GROSSC.DNET.NASA.GOV

10:45 -- 11:15
Concept Formation in Temporally Structured Domains
Wayne Iba
Recom Technologies
NASA Ames Research Center
Mail Stop 269-2
Moffett Field, CA 94035-1000
415-604-4721
IBA@PTOLEMY.ARC.NASA.GOV

Afternoon Session
Building N203, Room 104
NASA Ames Research Center
(by Video Teleconference to other Centers)

Philip Laird, Chair
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Moffett Field, CA 94035-1000
415-604-3362
LAIRD@PTOLEMY.ARC.NASA.GOV

12:10 -- 12:40
Results of the Santa Fe Time Series Competition
Andreas Weigend
Xerox Corp. and University of Colorado, Boulder
Xerox PARC/SSL
3333 Coyote Hill Road
Palo Alto, CA 94304
(408) 812-4765
WEIGEND@PARC.XEROX.COM

12:40 -- 1:05
Shallow and Deep Knowledge Techniques for Diagnosis of Time Dependent Data
Steve Chien, Nicolas F. Rouquette, Richard Doyle, Leonard K. Charest, Jr., and E. Jay Wyatt
NASA Jet Propulsion Laboratory
Pasadena, CA 91109, USA
818-306-6144
CHIEN@AIG.JPL.NASA.GOV

1:05 -- 1:30
Neural Networks for Prediction
Claudia Meyer
Sverdrup Technology
NASA Lewis Research Center
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Cleveland, OH 44135
216-433-7511
SPMLM@VENUS.LERC.NASA.GOV

1:30 -- 1:55
System Trend Analysis Reduction Tool
W. Joseph Elliott
Analex Systems, Inc.
P.O. Box 21206
Kennedy Space Center, FL 32818-0206
407-861-0913
Fax: 407-861-5774

1:55 -- 2:20
Current Trend Analysis Activities at
Goddard Space Flight Center
Walt Truszkowski and Troy Ames (GSFC),
Sid Bailin and Scott Henderson (CTA Inc.)
Code 522.3
NASA Goddard Space Flight Center
Greenbelt, MD 20771
301-286-7896
WTRUSZKOWSKI.520@POSTMAN.GSFC.NASA.GOV

2:20 -- 2:45
Predictive Information Research for Aircraft
Fault Management
Anna Trujillo
NASA Langley Research Center
Hampton, VA 23665
804-864-8047
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3:30 -- 4:30

Discussion Session
Building N213, Room 261
NASA Ames Research Center

Padhraic Smyth, Chair
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May 12, 1993
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NASA Workshop on Automation of Time Series, Signatures, and Trend Analysis
May 12, 1993
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May 12, 1993

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NASA Workshop on Automation of Time Series, Signatures, and Trend Analysis
May 12, 1993

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A Health Monitoring Expert System

June Zakrajsek,
NASA Lewis

A health monitoring expert system software architecture has been developed to support condition-based health monitoring of rocket engines. It's first application is to the Space Shuttle Main Engine. The Post-Test Diagnostic System (PTDS) runs offline, using as input the data recorded from hundreds of sensors. The system is invoked after a test has completed, and produces suggestions, analysis, and an organized graphical presentation of the data with important effects highlighted.

The analysis that is performed within the PTDS for the SSME are feature driven. Classical techniques have been used to develop general routines that detect features, such as drifts, spikes, level shifts, erratic, excessive noise, peaks, and different-than. These techniques provide the features required by the PTDS, but require approximately twenty minutes of processing time, and considerable effort in determining the feature thresholds.

The overall expert system architecture has been developed and documented so that expert modules analyzing other components can be easily added. The architecture emphasizes modularity, reusability, and open system interfaces so that it may be used to analyze other systems as well.

POST TEST DIAGNOSTIC SYSTEM

A HEALTH MONITORING EXPERT SYSTEM

Presentation For

NASA Workshop on Automation of Time Series, Signatures and Trend Analysis

May 12, 1993

By

June Zakrajsek

NASA Lewis Research Center
(216) 977-7470
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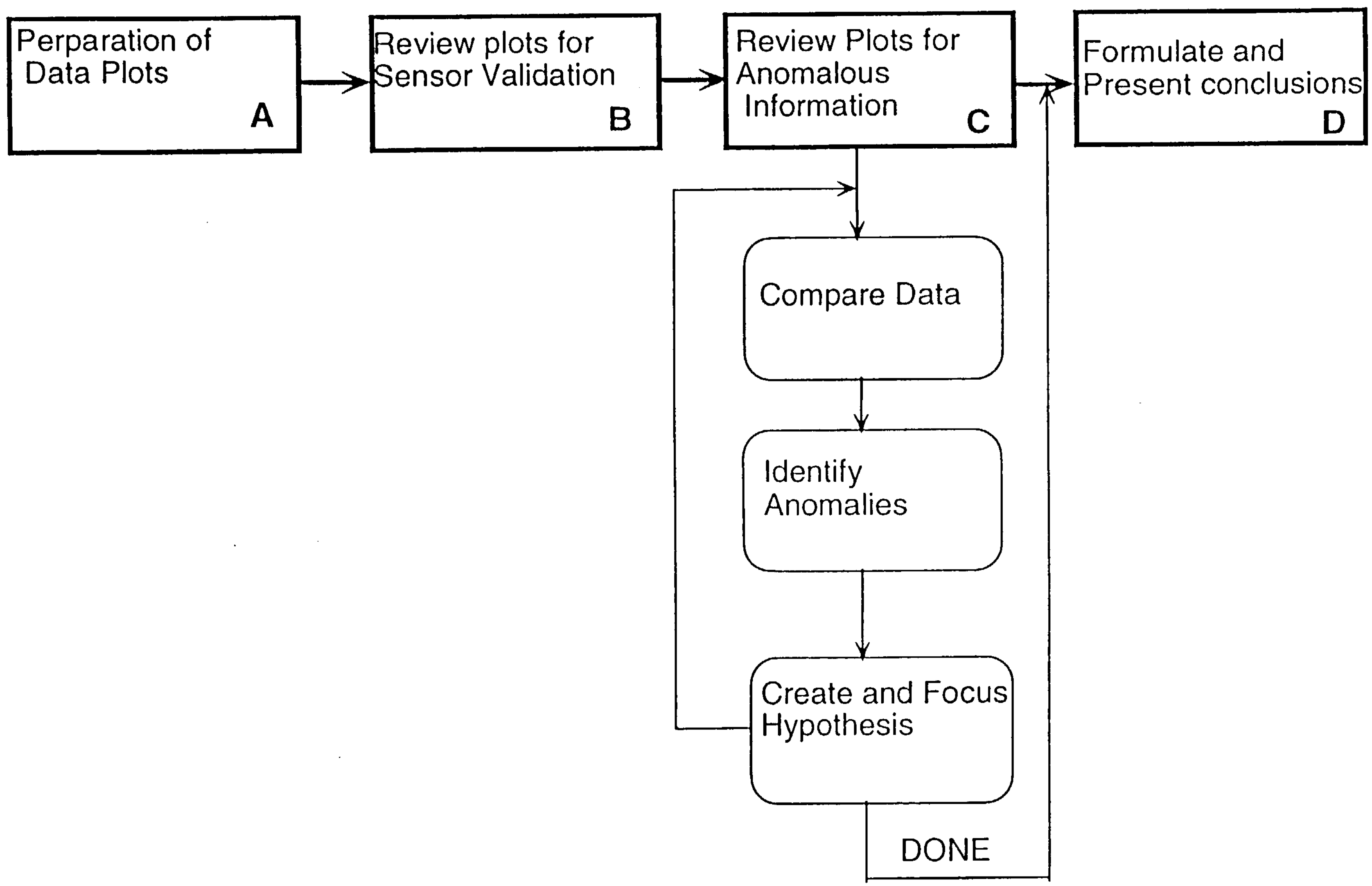
POST TEST DIAGNOSTIC SYSTEM (PTDS)

PROBLEM

- After flight and firing of a rocket engine a considerable effort is spent analyzing data to determine if test objectives were met, and if anomalous conditions or failures occurred.

- Data review process is labor intensive and time consuming.

POST TEST DIAGNOSTIC SYSTEM (PTDS)



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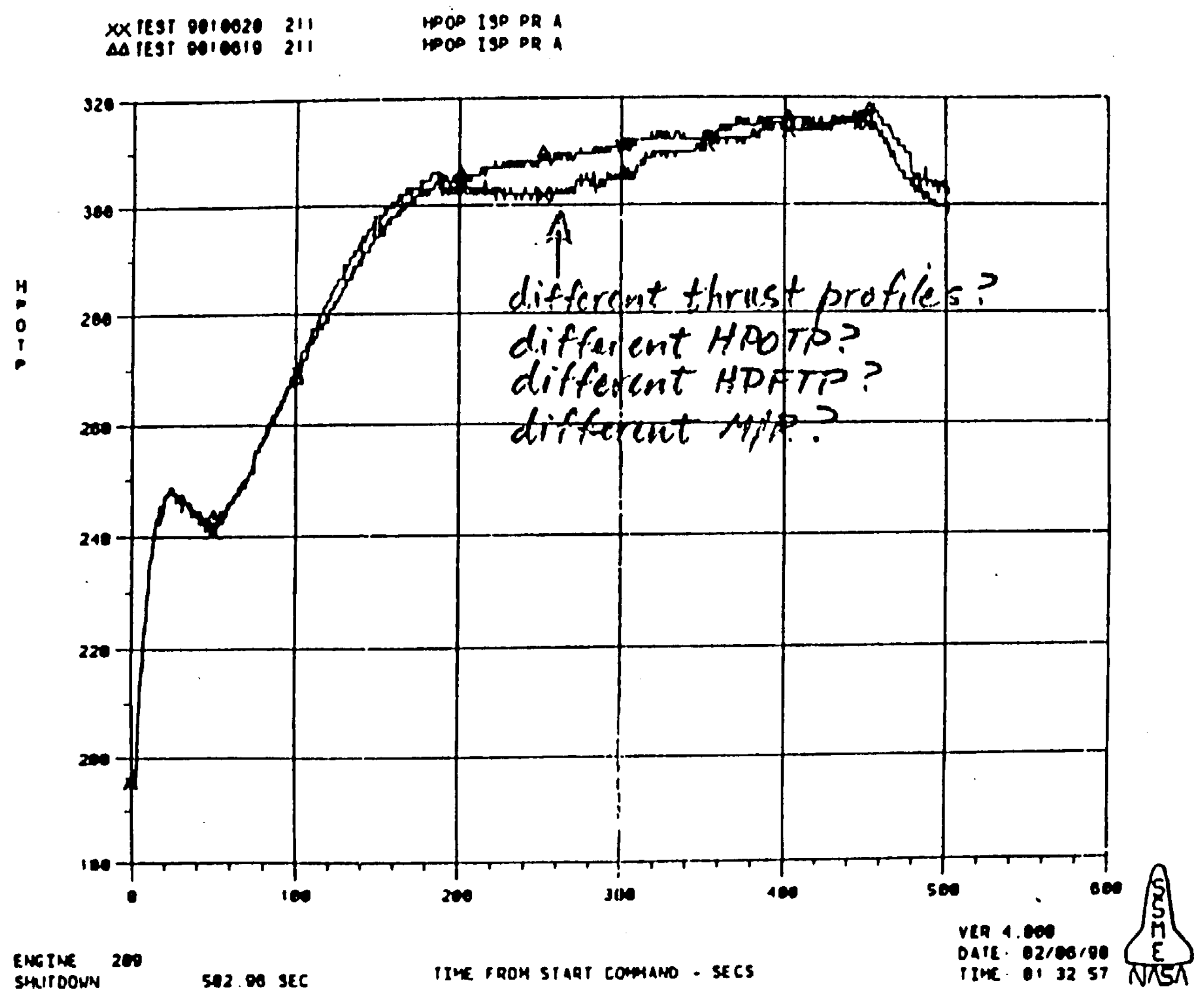
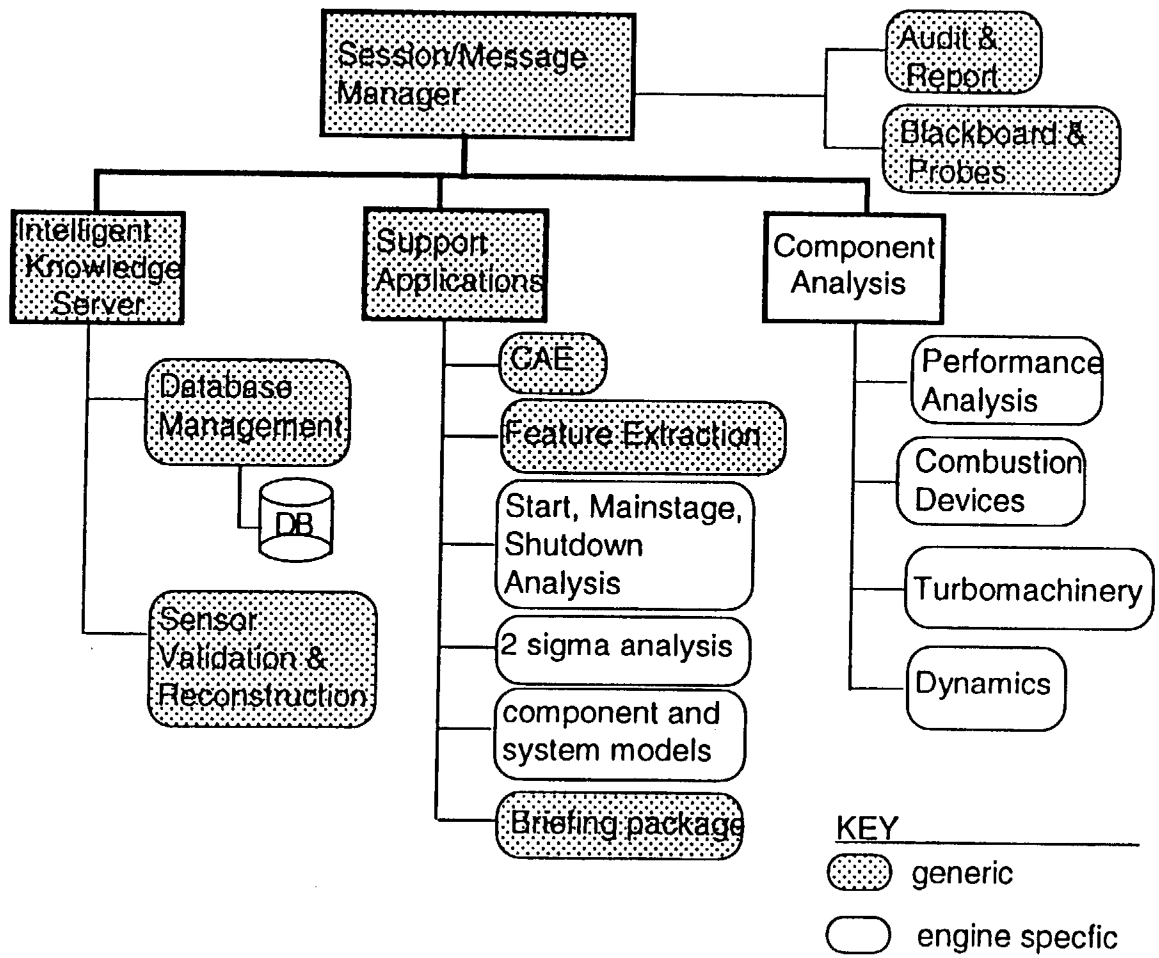


POST TEST DIAGNOSTIC SYSTEM (PTDS)

BENEFITS

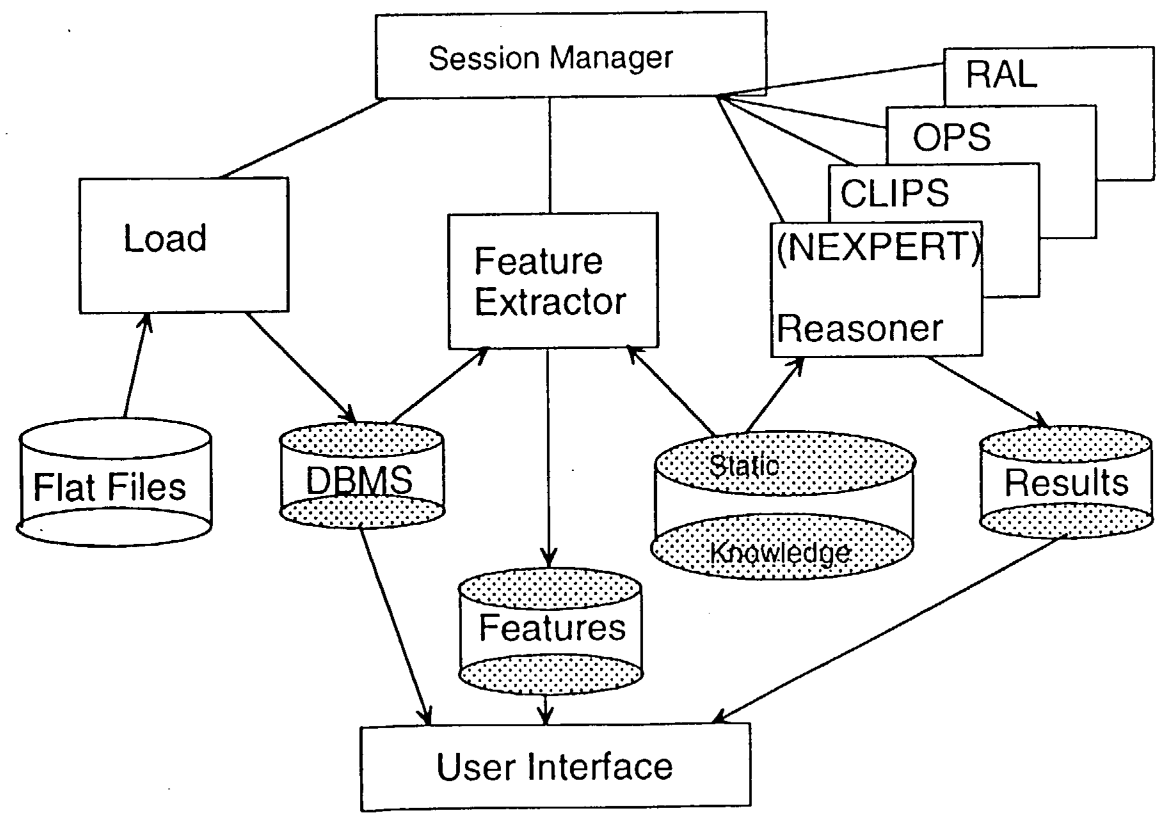
- Reduces manpower costs for post test data handling and analysis
- Reduces turn around time between tests and flights
- Captures available human expertise
- Increases repeatability of analysis
- Provides a training mechanism for new data analysts

POST TEST DIAGNOSTIC SYSTEM (PTDS)



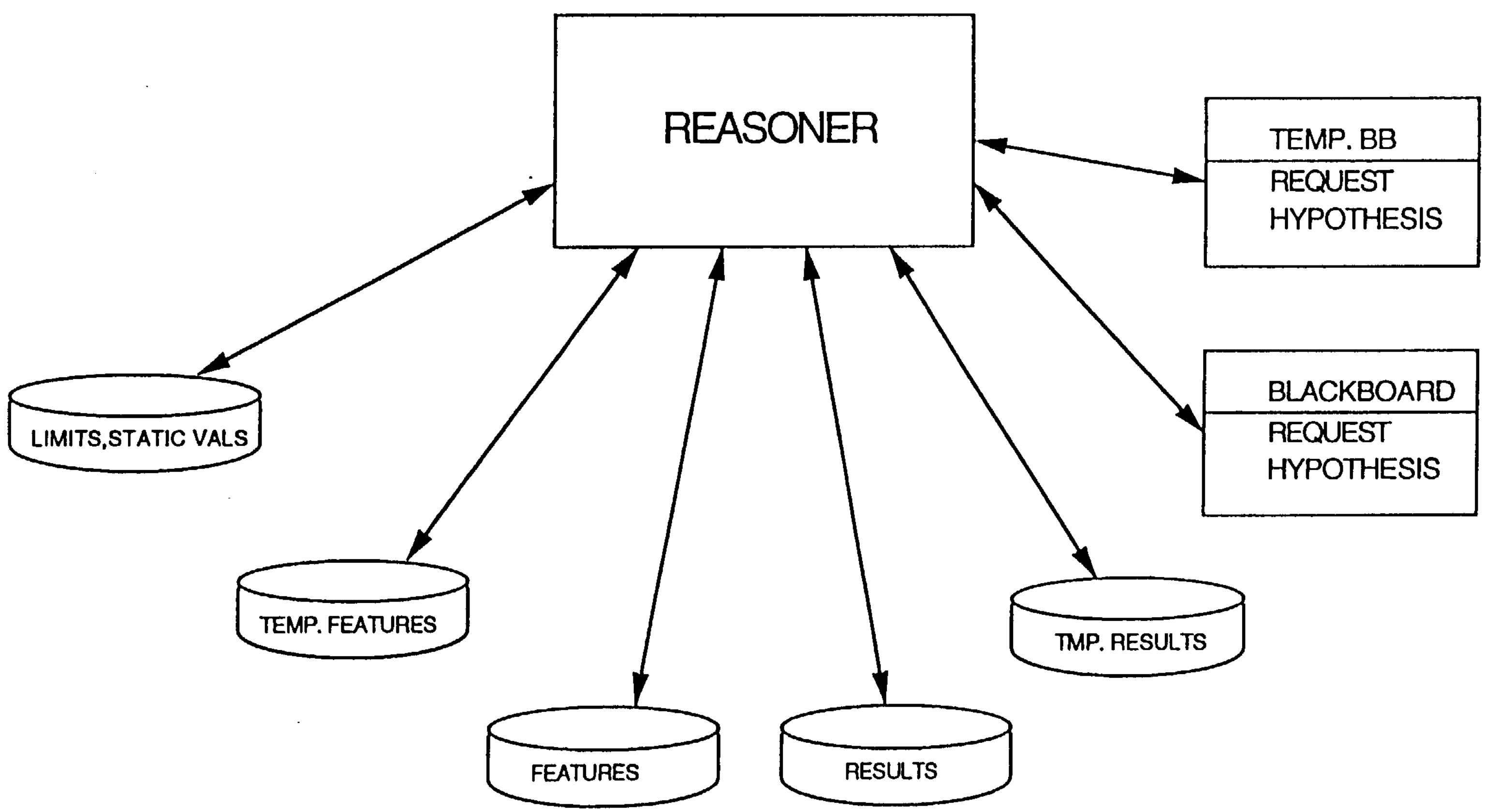
POST TEST DIAGNOSTIC SYSTEM (PTDS)

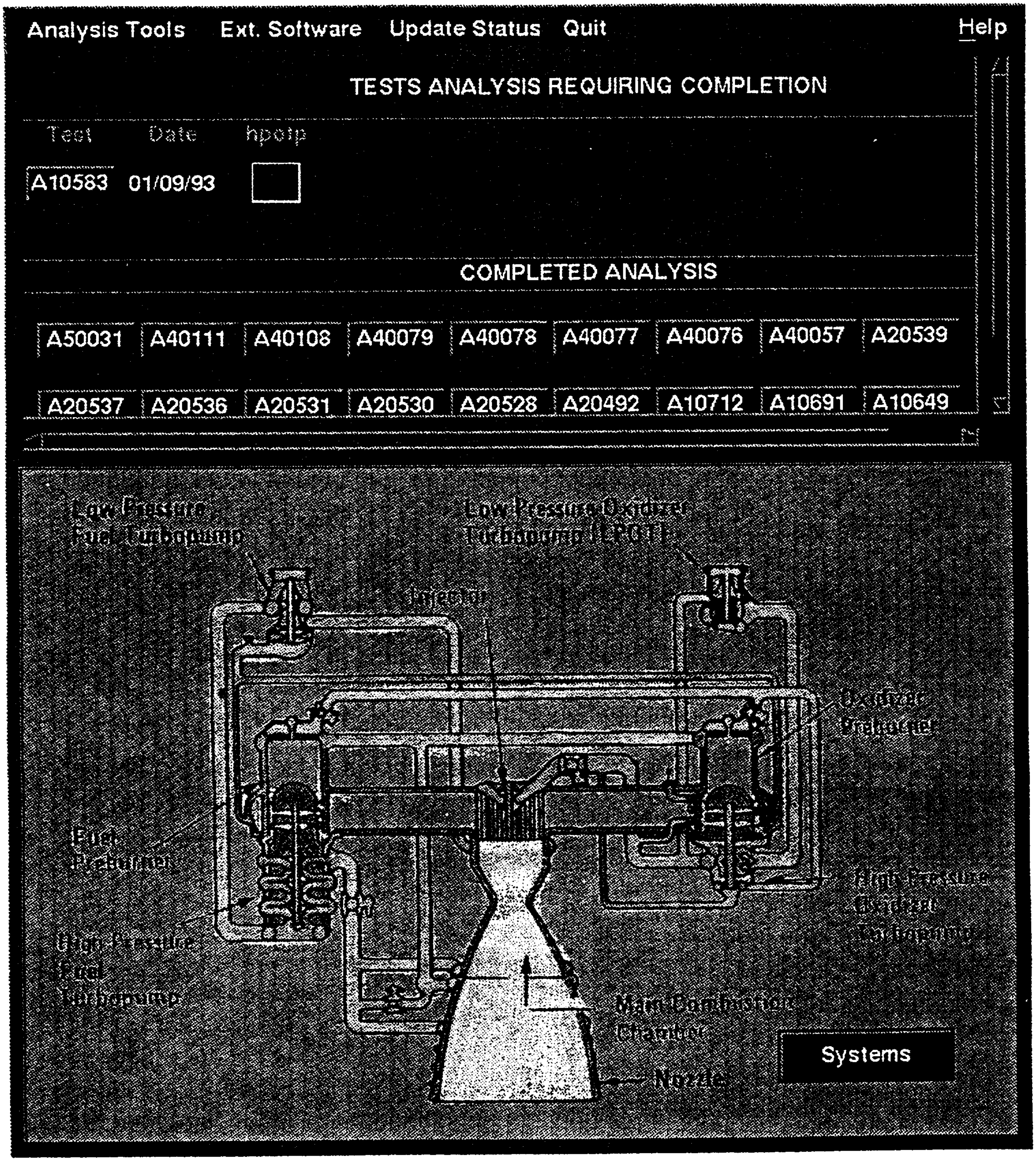
PTDS ARCHITECTURE OVERVIEW

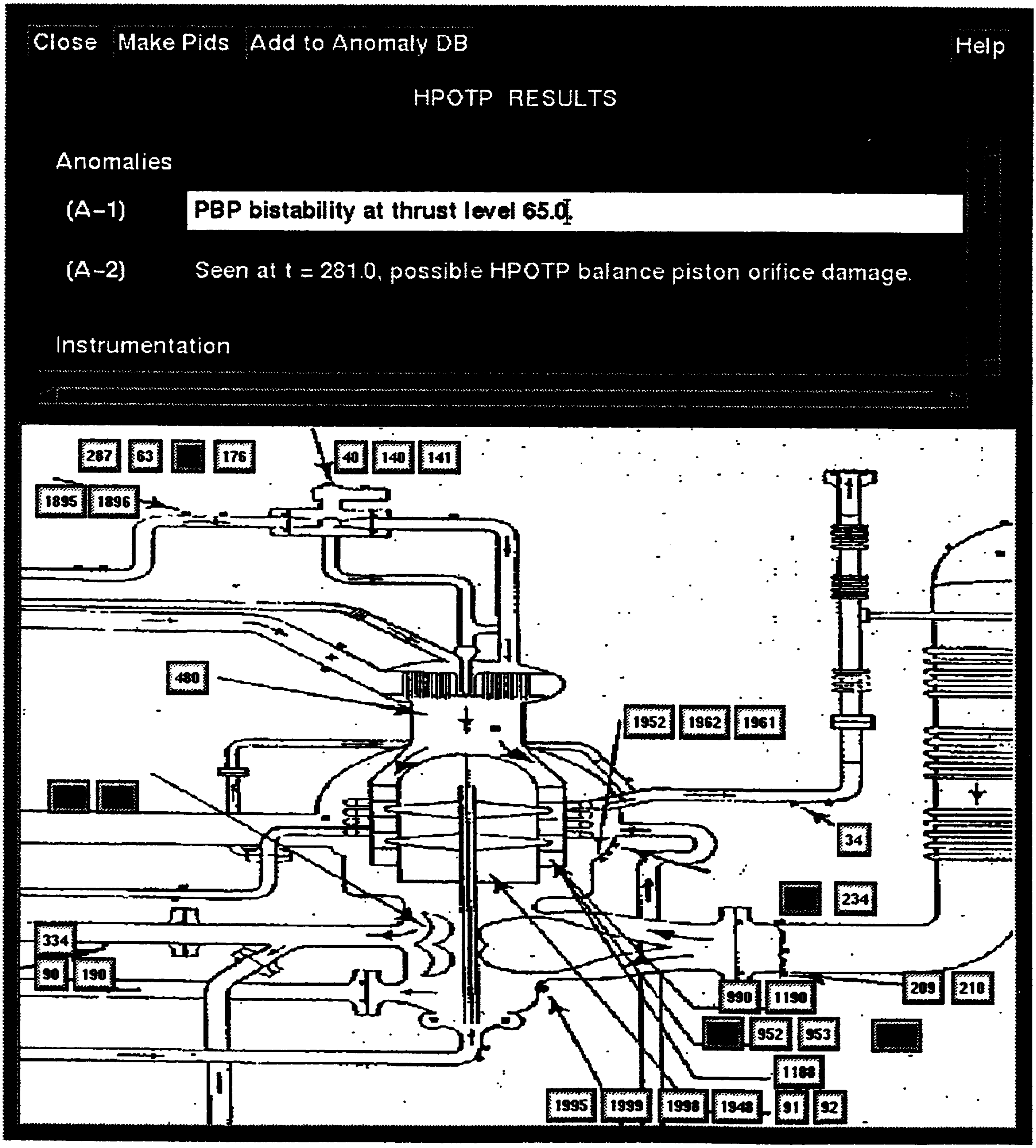


POST TEST DIAGNOSTIC SYSTEM (PTDS)

PTDS REASONER MODULE OVERVIEW




Analysis Tools
Ext. Software
Update Status
Quit
Help
TESTS ANALYSIS REQUIRING COMPLETION
Test
Date
hpotp
A10583
01/09/93
COMPLETED ANALYSIS
A50031
A40111
A40108
A40079
A40078
A40077
A40076
A40057
A20539
A20537
A20536
A20531
A20530
A20528
A20492
A10712
A10691
A10649
Low Pressure Fuel Turbopump
Low Pressure Oxidizer Turbopump (LPOT)
Injector
Oxidizer Preburner
Fuel Preburner
High Pressure Oxidizer Turbopump
High Pressure Fuel Turbopump
Main Combustion Chamber
Nozzle
Systems


Close
Make Pids
Add to Anomaly DB
Help
HPOTP RESULTS
Anomalies
(A-1)
PBP bistability at thrust level 65.0
(A-2)
Seen at t = 281.0, possible HPOTP balance piston orifice damage.
Instrumentation
287
63
176
40
140
141
1895
1896
480
1952
1962
1961
34
234
334
90
190
209
210
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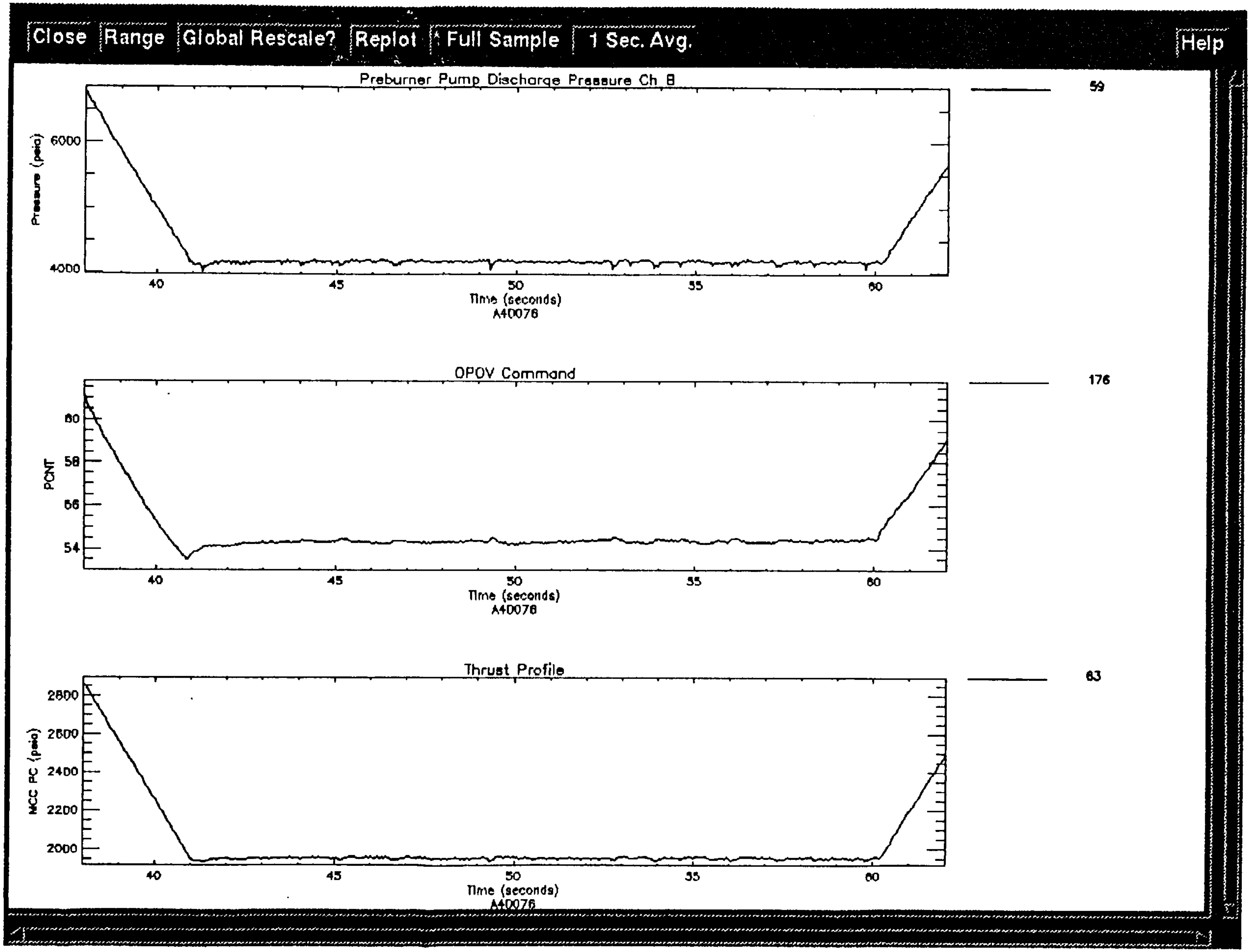
1999
1998
1948
91
92


Close
Range
Global Rescale?
Replot
Full Sample
1 Sec. Avg.
Help
Preburner Pump Discharge Pressure Ch B
Pressure (psia)
6000
4000
40
45
50
55
60
Time (seconds)
A40076
59
OPOV Command
PCNT
60
58
56
54
Time (seconds)
A40076
176
Thrust Profile
MCC PC (psia)
2800
2600
2400
2200
2000
Time (seconds)
A40076
63

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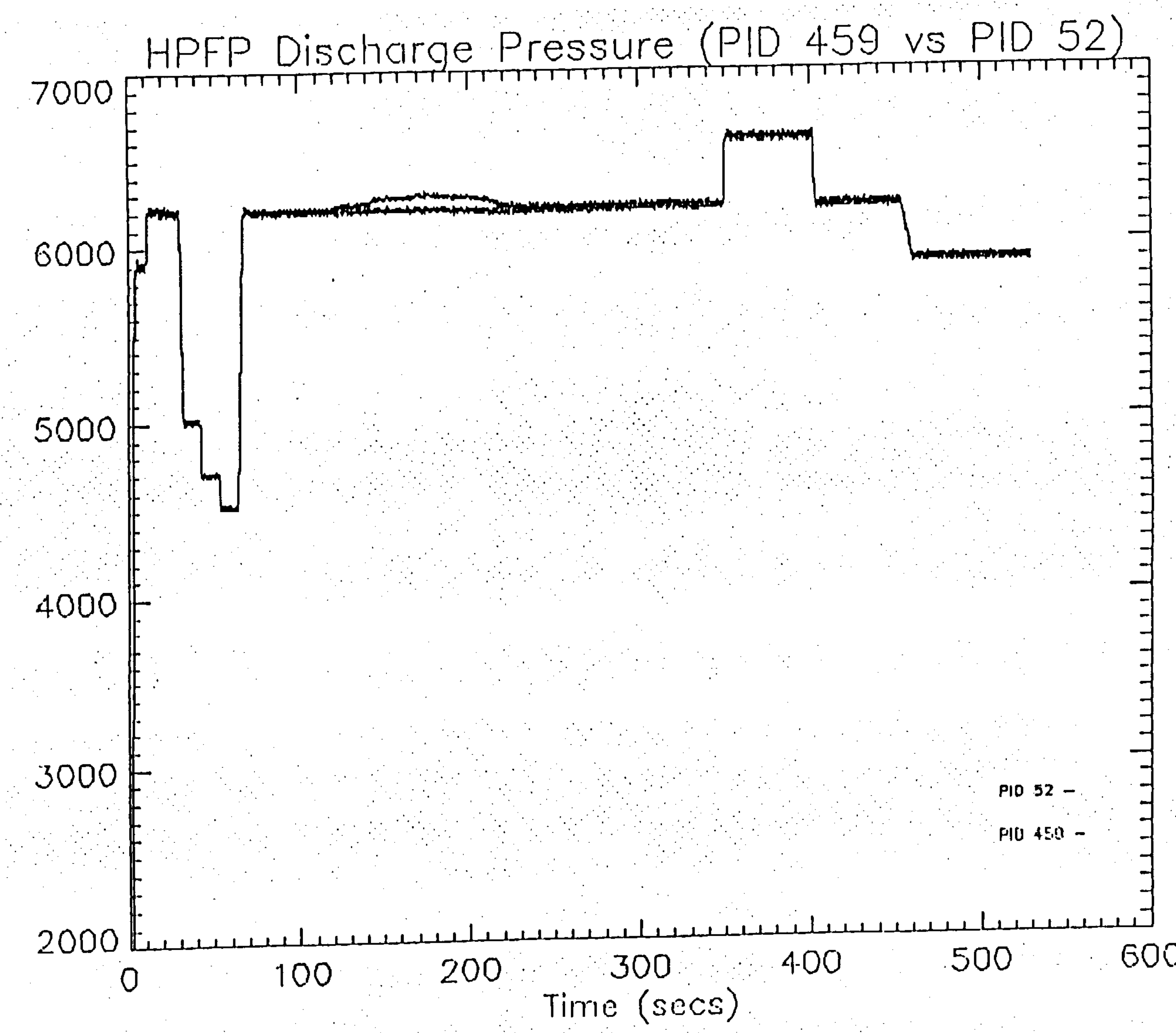
POST TEST DIAGNOSTIC SYSTEM (PTDS)

APPLIED TO AN SSME TEST AT STENNIS SPACE CENTER

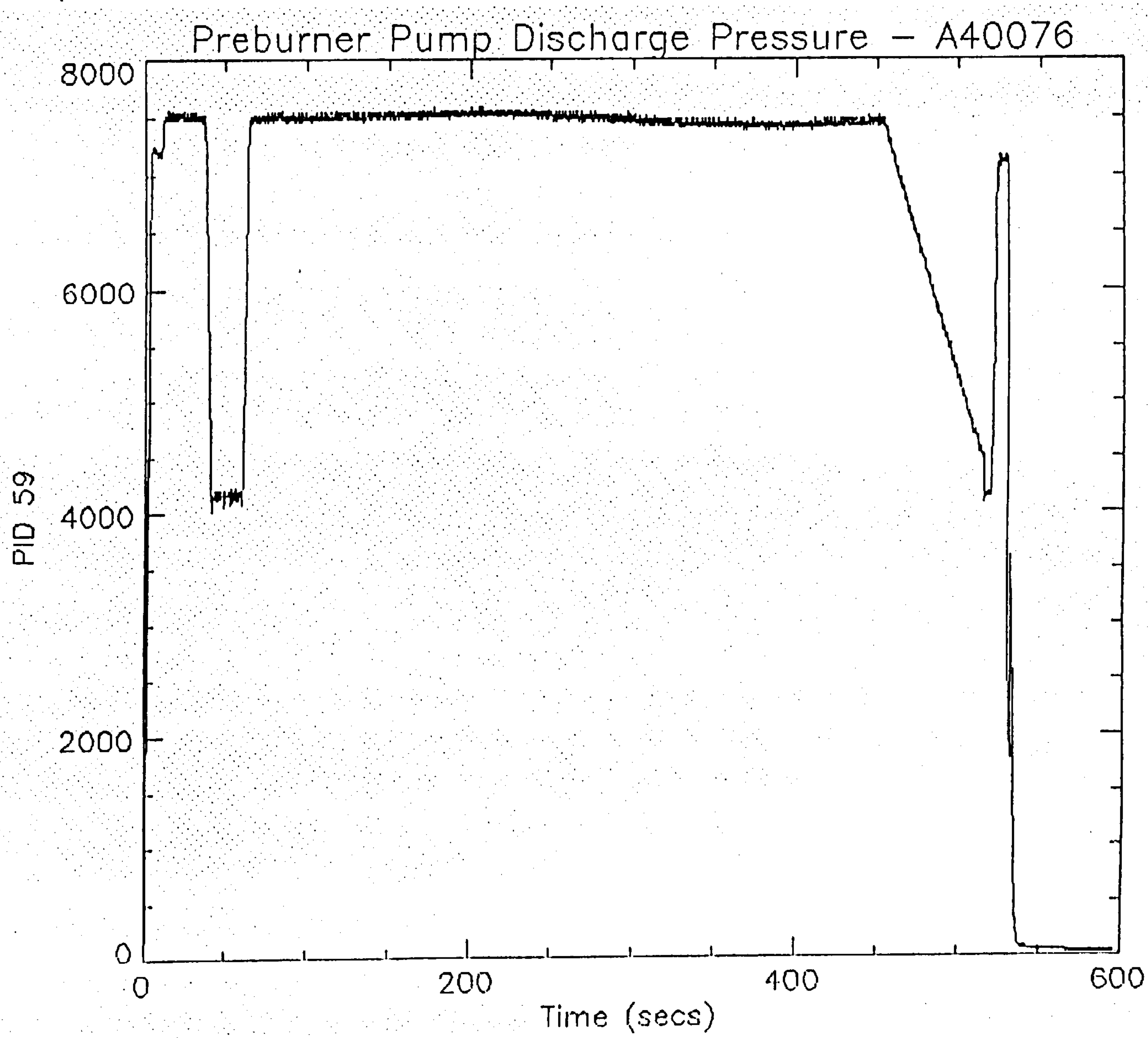
SSME DATA ANALYSIS AREAS	CURRENT MANUAL PROCESS	PTDS - AUTOMATED PROCESS	NUMBER OF PARAMETERS ANALYZED (NUMBER OF MEASUREMENTS USED)
PERFORMANCE/OVERALL SYSTEM	28 HRS	[1]	50 (105)
COMBUSTION DEVICES	2 HRS	[2]	8 (22)
TURBOMACHINERY - HPOTP	TOTAL OF 3 HRS	2 MIN.	15 (27)
HPFTP		[3]	10 (22)
LPDTP		[4]	8 (15)
LPFTP		[4]	9 (19)
DYNAMICS	16 HRS	[4]	UNKNOWN
DATA PREPARATION	20 HRS	3 HRS 50 MIN.	N/A
TOTAL	39 HRS	3 HRS 52 MIN.	50 (105)

[1] CURRENTLY BEING IMPLEMENTED.
[2] TO BE POSSIBLY IMPLEMENTED UNDER CODE Q FUNDING - START FY94.
[3] TO BE IMPLEMENTED UNDER CODE D FUNDING - START FY94.
[4] CURRENTLY NOT BEING WORKED.

POST TEST DIAGNOSTIC SYSTEM (PTDS)

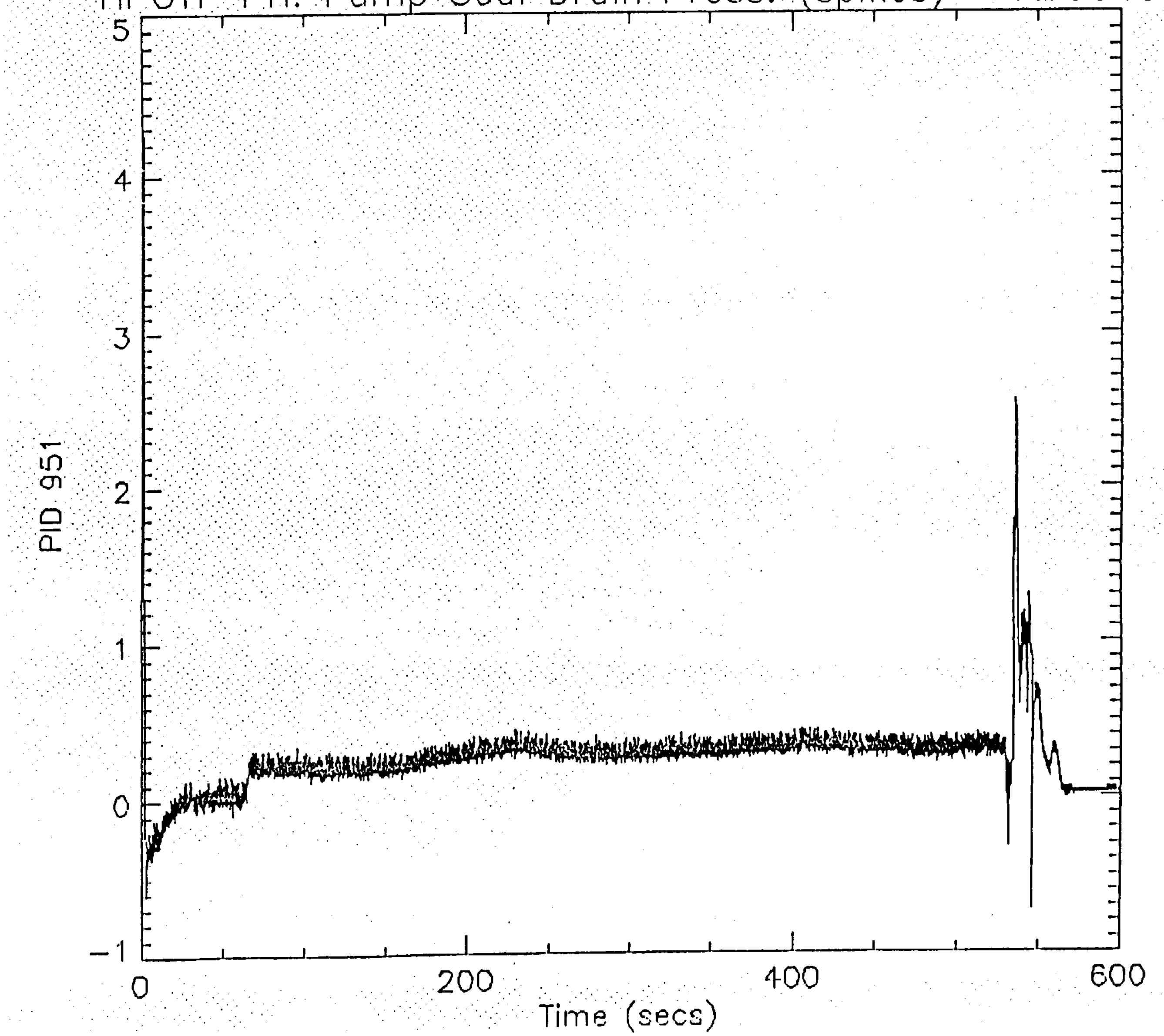


POST TEST DIAGNOSTIC SYSTEM (PTDS)

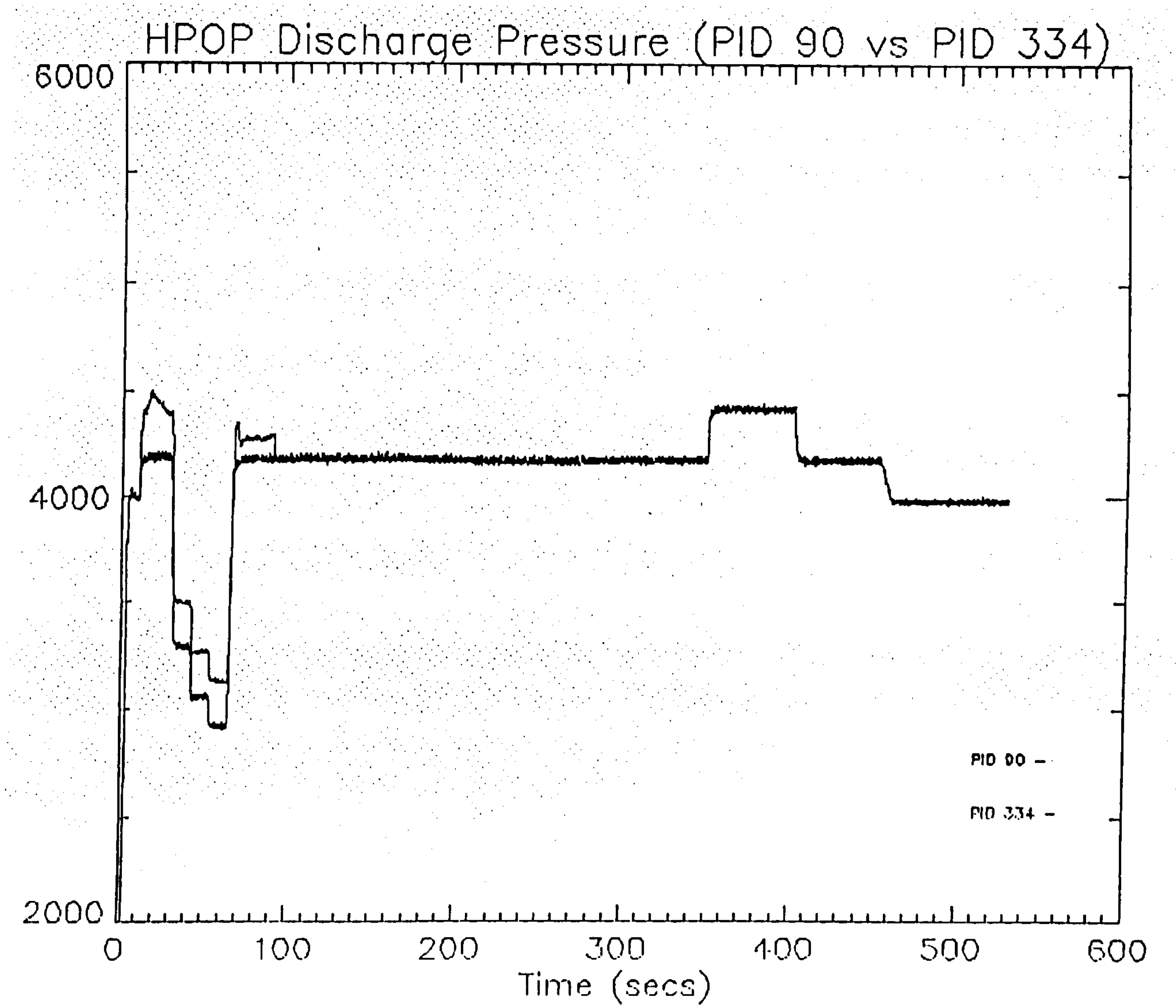


POST TEST DIAGNOSTIC SYSTEM (PTDS)

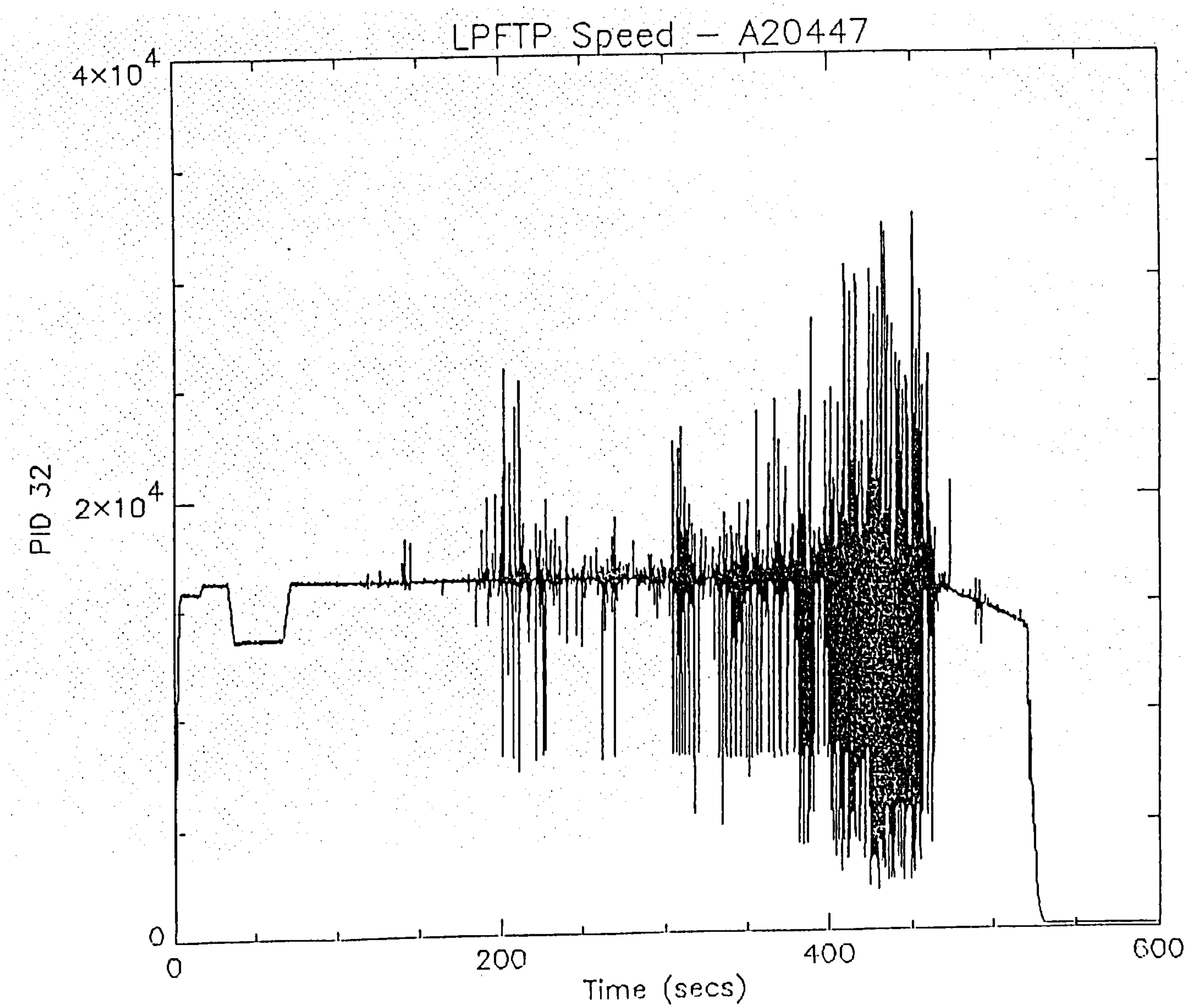
HPOTP Pri. Pump Seal Drain Press. (spikes) – A10649



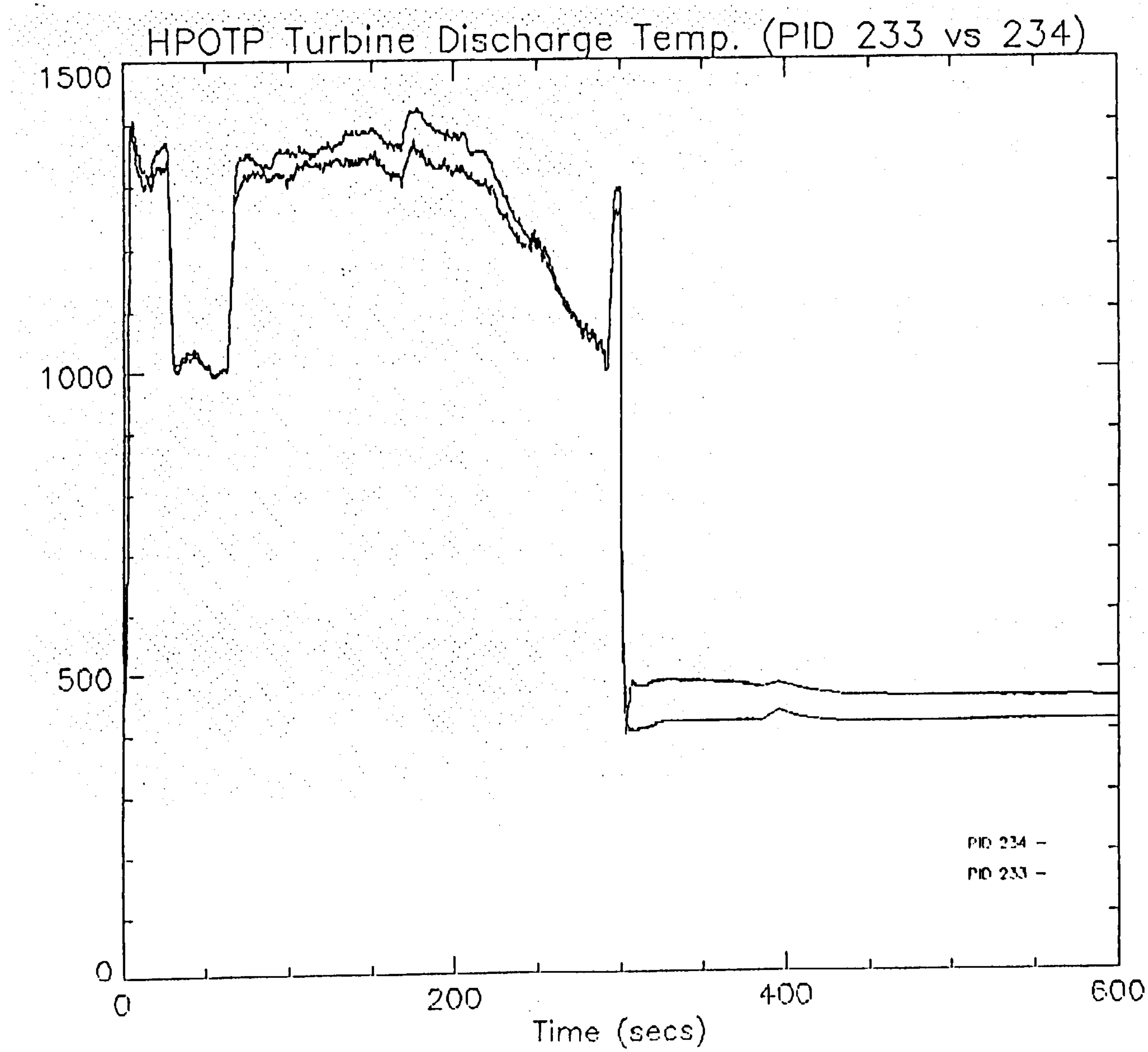
POST TEST DIAGNOSTIC SYSTEM (PTDS)



POST TEST DIAGNOSTIC SYSTEM (PTDS)



POST TEST DIAGNOSTIC SYSTEM (PTDS)



POST TEST DIAGNOSTIC SYSTEM (PTDS)

FEATURE	EXTRACTION METHOD
Drift[1][2]	ABS(m)>Threshold
Spike	ABS[y(i)-y(i-1)] > Threshold
Level Shift[2]	Derivative > Threshold where: Duration <= 1 Sec
Excessive Noise[1]	Sigma (Data-Curvefit) < Threshold
Erratic[1]	StdDevFit +/- ExpectedSigma
Different-Than[2]	DeltaAvg < Threshold
Peak[1][2]	m(tangent line) >< 3*Sigma where: magnitude >= threshold; width >= threshold

[1] Curvefitting routine based on Numerical Recipes routine "mrqmin"
[2] Routine uses smoothed data.

POST TEST DIAGNOSTIC SYSTEM (PTDS)

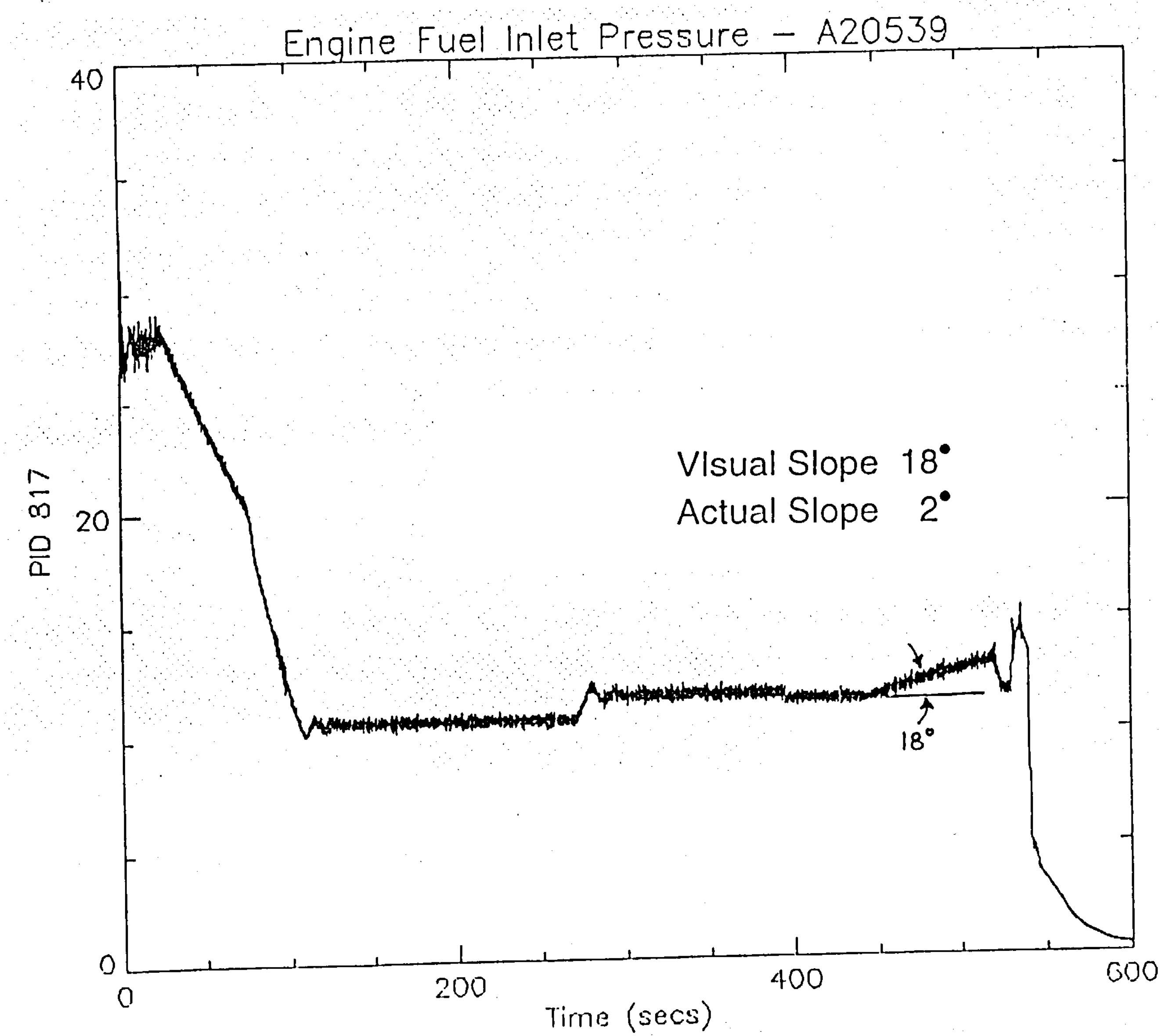
ISSUES

<u>Accurate Identification of Features</u>

- Transformation (Visual to Numerical)
- Threshold Determination
- Data Variation
  - Test -Test Variation
  - Bit Toggle
  - Sensor Variation
  - Superpositioning
- Flexibility
  - User Definitions
  - Parameters

<u>Minimum Computation Time</u>

POST TEST DIAGNOSTIC SYSTEM (PTDS)



POST TEST DIAGNOSTIC SYSTEM (PTDS)

SUMMARY

- PTDS designed to aid analysts in the review of test data
- PTDS designed to be generic to allow system specific modules to be added
- Current work adding SSME specific knowledge
- All reasoning performed on features.

A Pattern Recognition Toolkit for Analyzing Signatures in Shuttle Telemetry Data

Dave Hammen
The MITRE Corporation
1120 NASA Road 1 Houston, TX
e-mail: dhammen@mitre.org

Several flight control positions examine plots of Shuttle telemetry data on paper strip chart recorders (SCRs). These plots graphically portray on-board activities, which helps the controllers in their decision-making process. Controllers identify trends and events on the SCRs by recognizing patterns in the plots. For example, the Electrical Generation and Integrated Loading controllers deduce which electrical equipment has been turned on or off by examining the SCR plots of electrical current usage. The SCRs generate continuous plots, which the controllers value, but are costly to maintain. Workstation-based SCR emulations lack the key features (permanence, resolution, and size) of the paper plots, making controllers reluctant to give up the paper plots. While replacing the paper SCRs with on-screen emulations might reduce costs, this replacement would not reduce human involvement and cannot yet reproduce the resolution of the paper plots.

Automated signature detection and identification capabilities could perform some of the data interpretation tasks controllers do now, freeing the controllers to perform more important tasks. A workstation-based SCR tool that includes such automated signature detection and identification capabilities may reduce the need for the expensive paper SCRs. The short-term goal of this project is to apply several pattern recognition techniques to the electrical equipment recognition problem. We will then move on to another controller position. By applying pattern recognition techniques to a series of increasingly complicated Mission Control signature identification problems, we hope to move towards a general-purpose signature detection and identification capability. The ultimate goal of this project is to build a pattern recognition toolkit that will help build signature detection and identification applications. This project is jointly funded by the Real-Time Data System (RTDS) project and by the Software Technology Branch (STB) at NASA's Johnson Space Center, and involves personnel from RTDS, STB, NASA Ames Research Center, and the MITRE Corporation.

A Pattern Recognition Toolkit for Time Series Signature Analysis

Dave Hammen
(dhammen@mitre.org)

NASA Workshop on the Automation of Time Series, Signatures, and Trend Analysis

May 12, 1993

MITRE

Briefing Agenda

- Sample domain - problem definition
- Proposed solution
- Prototype architecture
- Accomplishments and near-term plans
- Genaralizing to a toolkit

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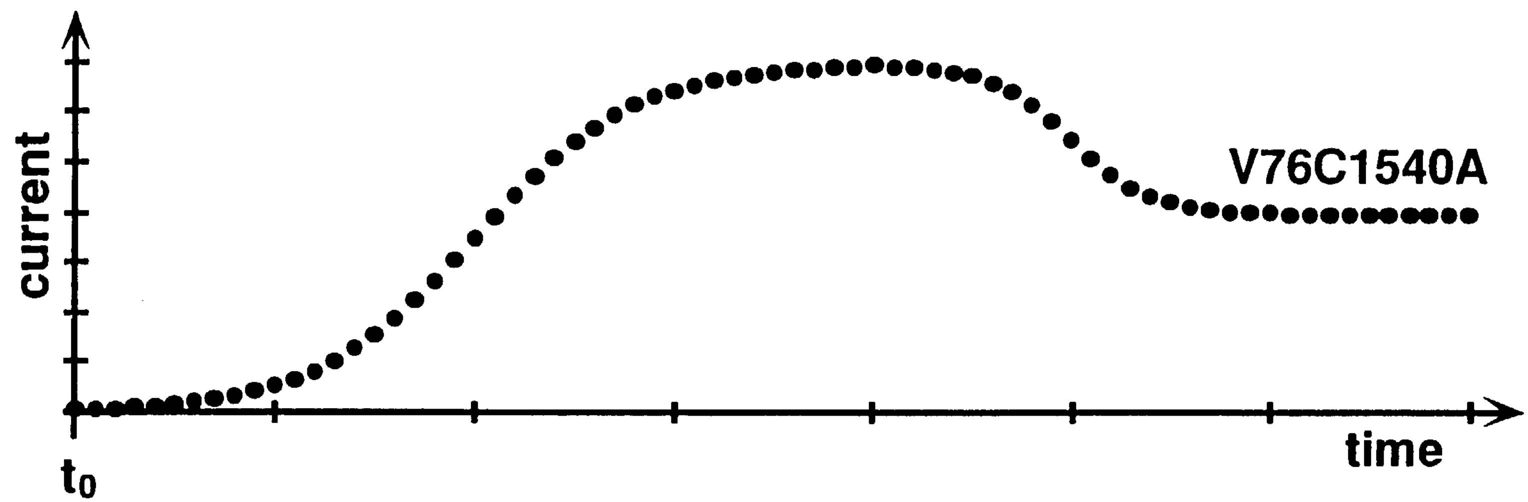
Downlinked Data



- AC power used on Shuttle by items such as fans, doors, and vacuum cleaners
- AC power usage sampled at 10 Hz onboard and monitored in Mission Control
- Shown: (invented) data for one phase of one AC power bus

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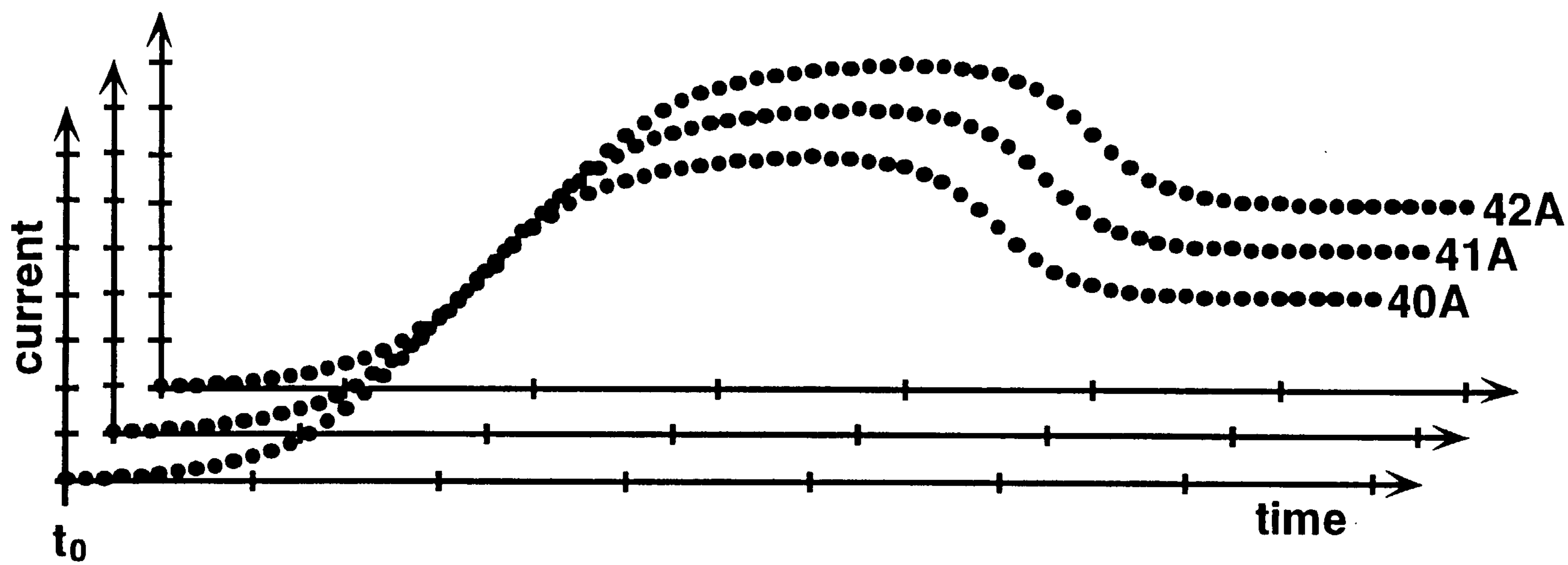
Downlinked Data (Concluded)



- Shuttle provides three-phase AC power
- Shown: data for one bus
- Three buses onboard => nine signals to analyze

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AC Motor Signatures

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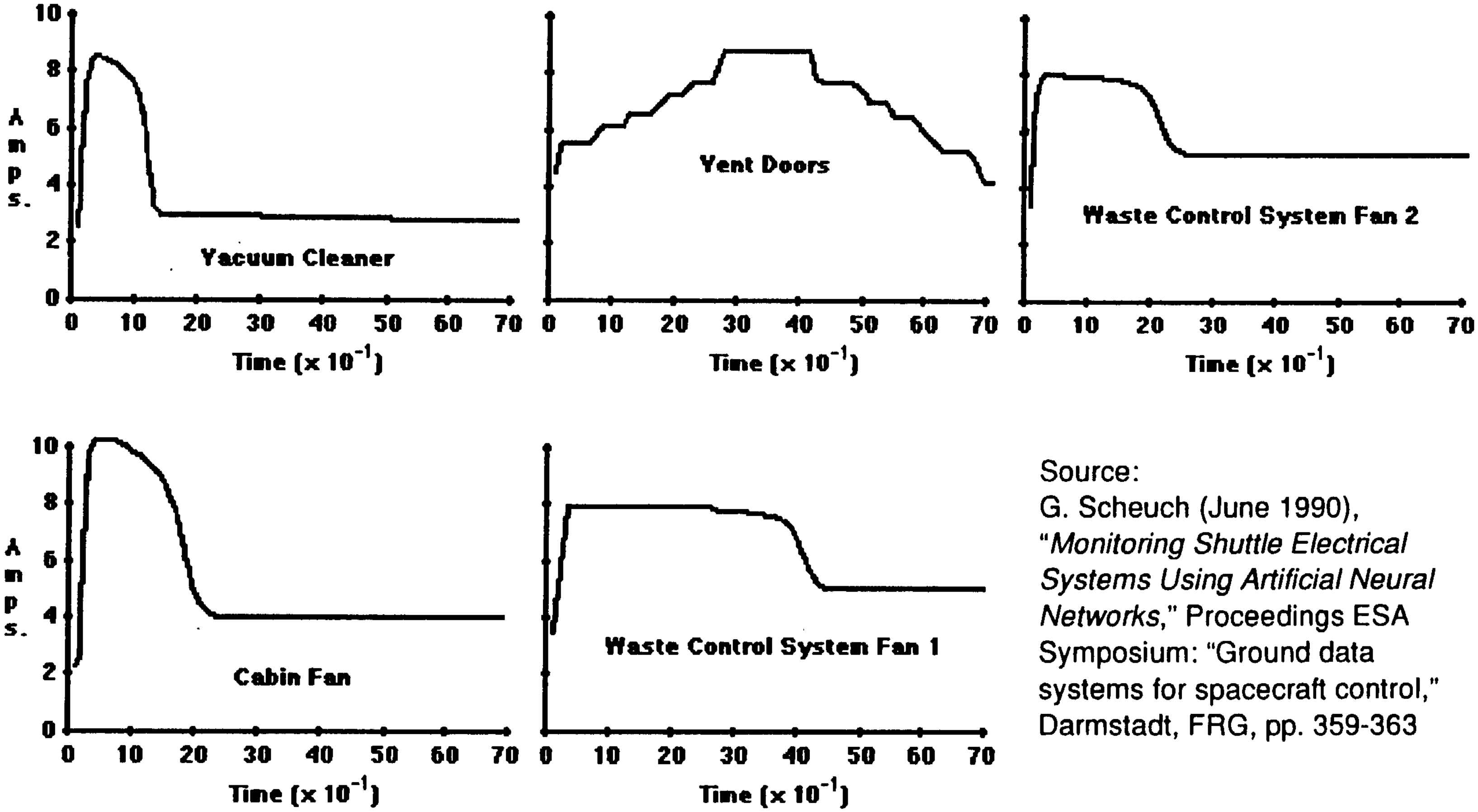
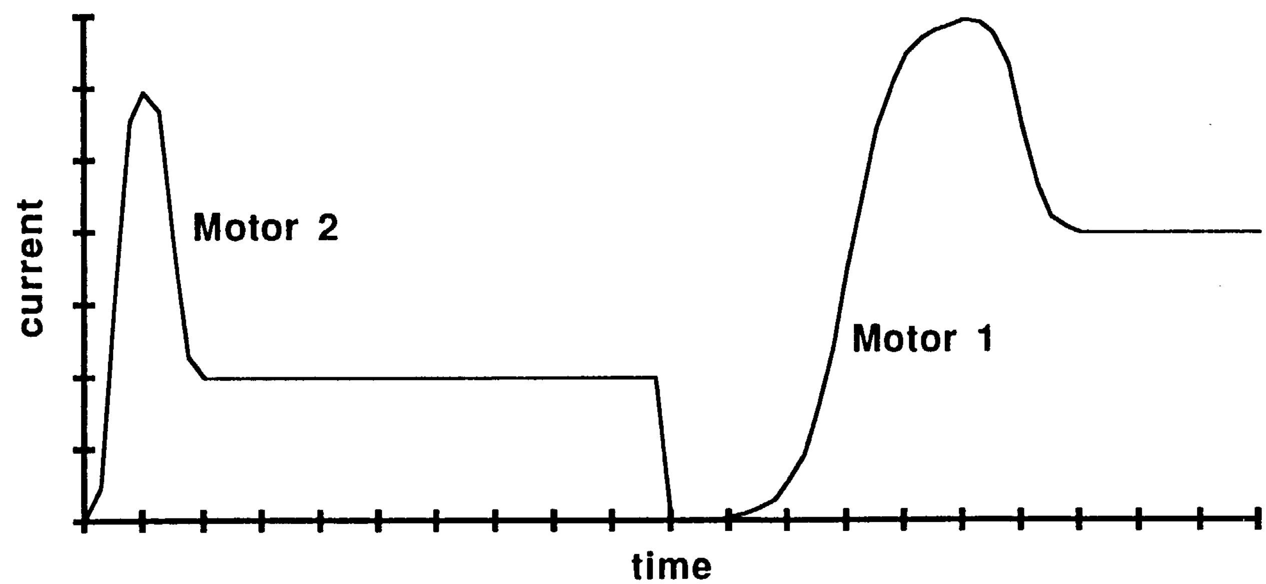


Source:
G. Scheuch (June 1990), "*Monitoring Shuttle Electrical Systems Using Artificial Neural Networks*," Proceedings ESA Symposium: "Ground data systems for spacecraft control," Darmstadt, FRG, pp. 359-363

Challenges



- If only signals arrived as shown above (clean and well-separated) ...
- But they don't. Next few charts illustrate some challenges

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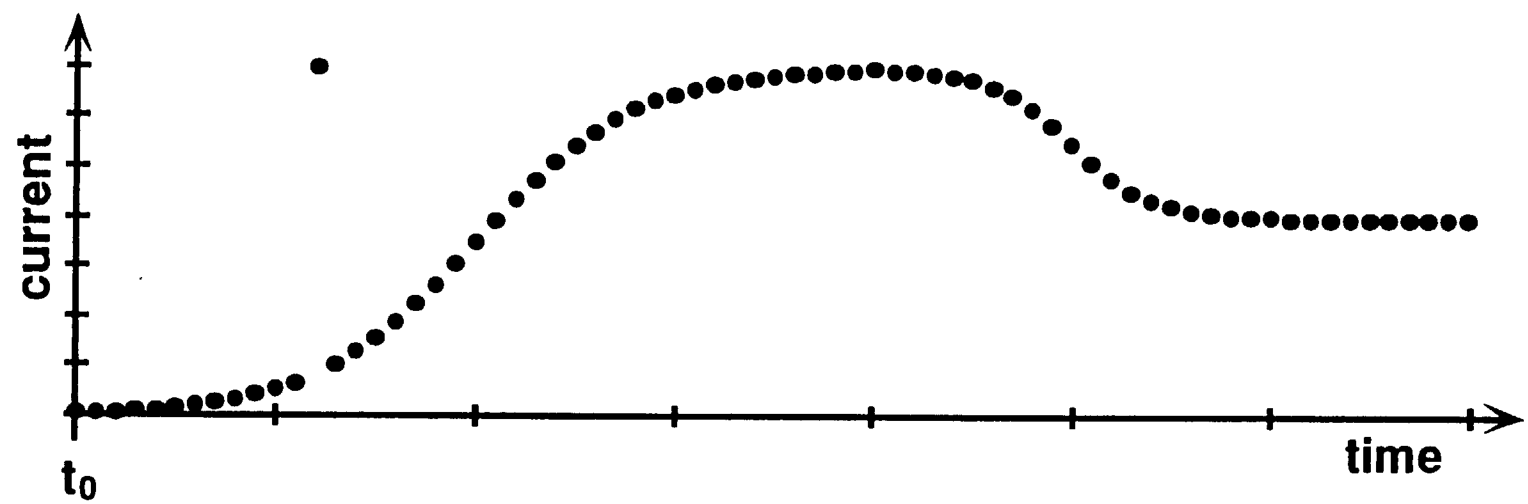
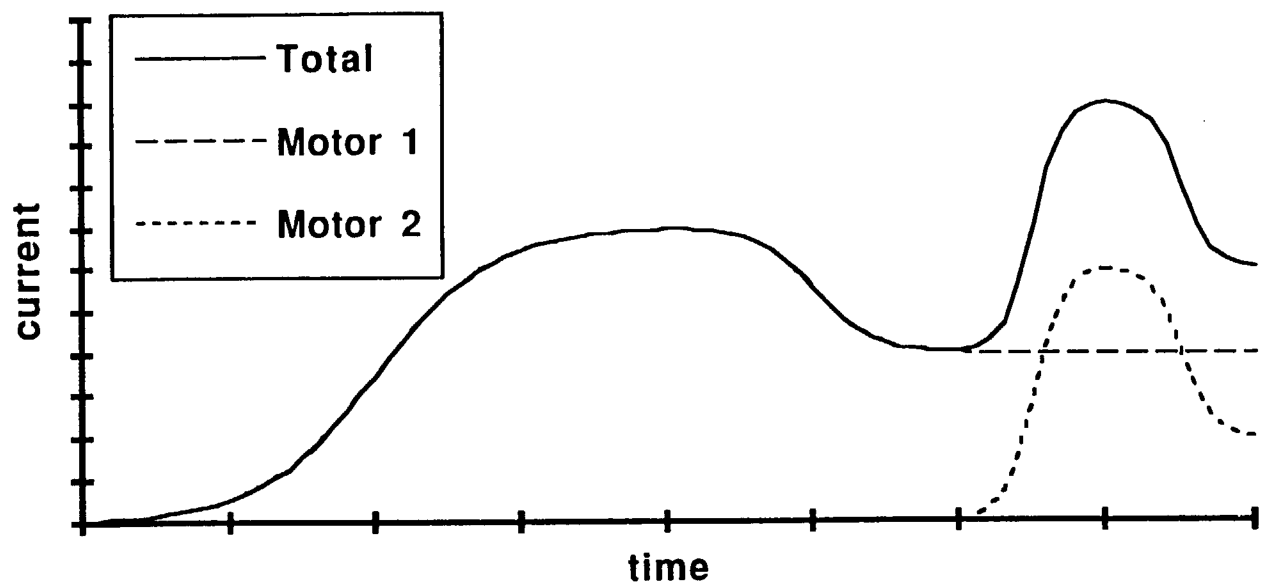
Noise



- Signals are noisy
  - Quantization noise (in this case, 0.08 amps.)
  - Data transmission noise (shown; non-Gaussian)
- Solutions
  - Sufficient number of sample signatures to accurately represent variations in signaturessuch as noise
  - Transmission noise filter to remove transmission noise

Simple Overlapping Signals



- Signatures overlap in time
- Simple signal superpositions occur while all but one motor are at steady-state (off or at constant run current value)
- Solution: Base current subtracted from signatures to force focus on changes in current usage

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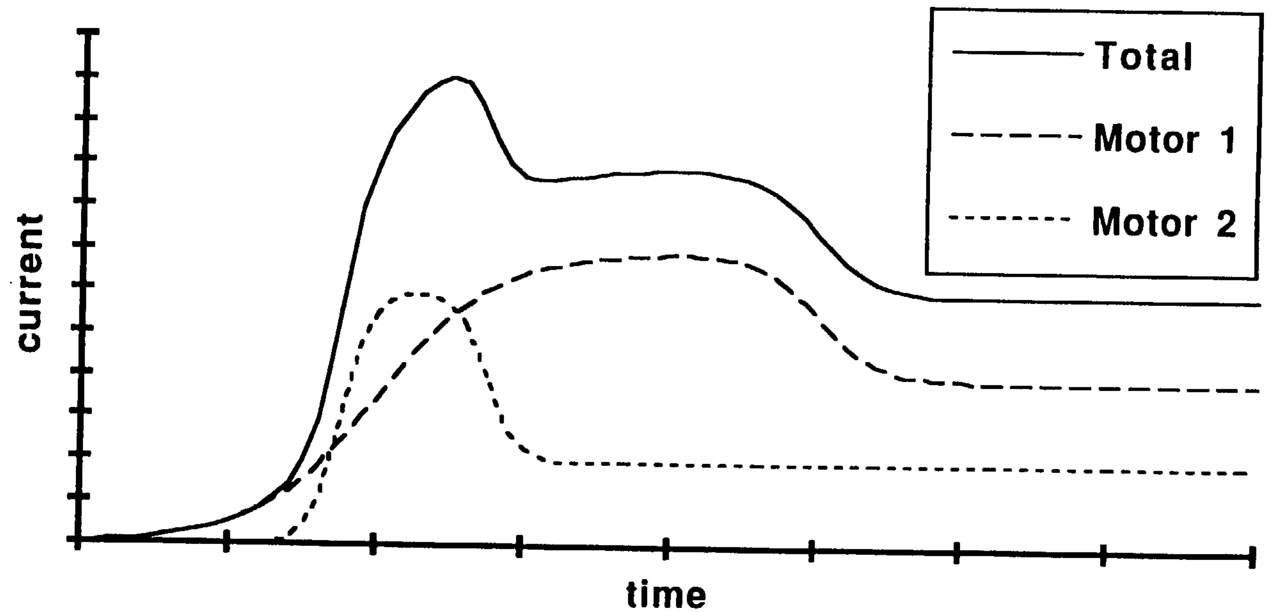
Complex Overlapping Signals



- More complex signal superpositions occur when multiple motors change state (start or stop) at nearly the same time
- Solution: Present unidentifiable signatures as "unidentified"

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Data Acquisition and Management

- Goal: Build real-time pattern recognition applications for variety of Shuttle data items

=> Solution: Reconfigurable data acquisition front-end to supply selected Shuttle telemetry data to pattern recognition module

- Constraint: Run application on workstation-class machine

=> Solution: Event detector to capture events for recognition

- Constraint: Simulated data inadequate for data-driven pattern recognition techniques

=> Solution: Event database containing captured events

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Problem Specification

- Power usage data collected onboard and transmitted to ground for display on strip chart recorders
- Shuttle has three buses to supply three-phase AC power to AC motors => nine signals to monitor
- EGIL controllers monitor strip charts for motor usage, anomalies
- Problem: Strip chart recorders are expensive to maintain, but on-screen alternatives are lacking
- Complicating factor: Real data are messy
- Need: Robust electrical motor signature analysis application

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Prototype Solution

- Many pattern recognition techniques exist
  - Artificial neural networks
  - Fuzzy logic
  - Inductive reasoning
  - Cross-correlation
  - Statistical techniques
- Expertise at JSC, Ames Research Center, and elsewhere
- Series of demonstrations of pattern recognition techniques
  - Data acquisition via Real-Time Data System
  - Test and demonstrate capabilities of individual techniques

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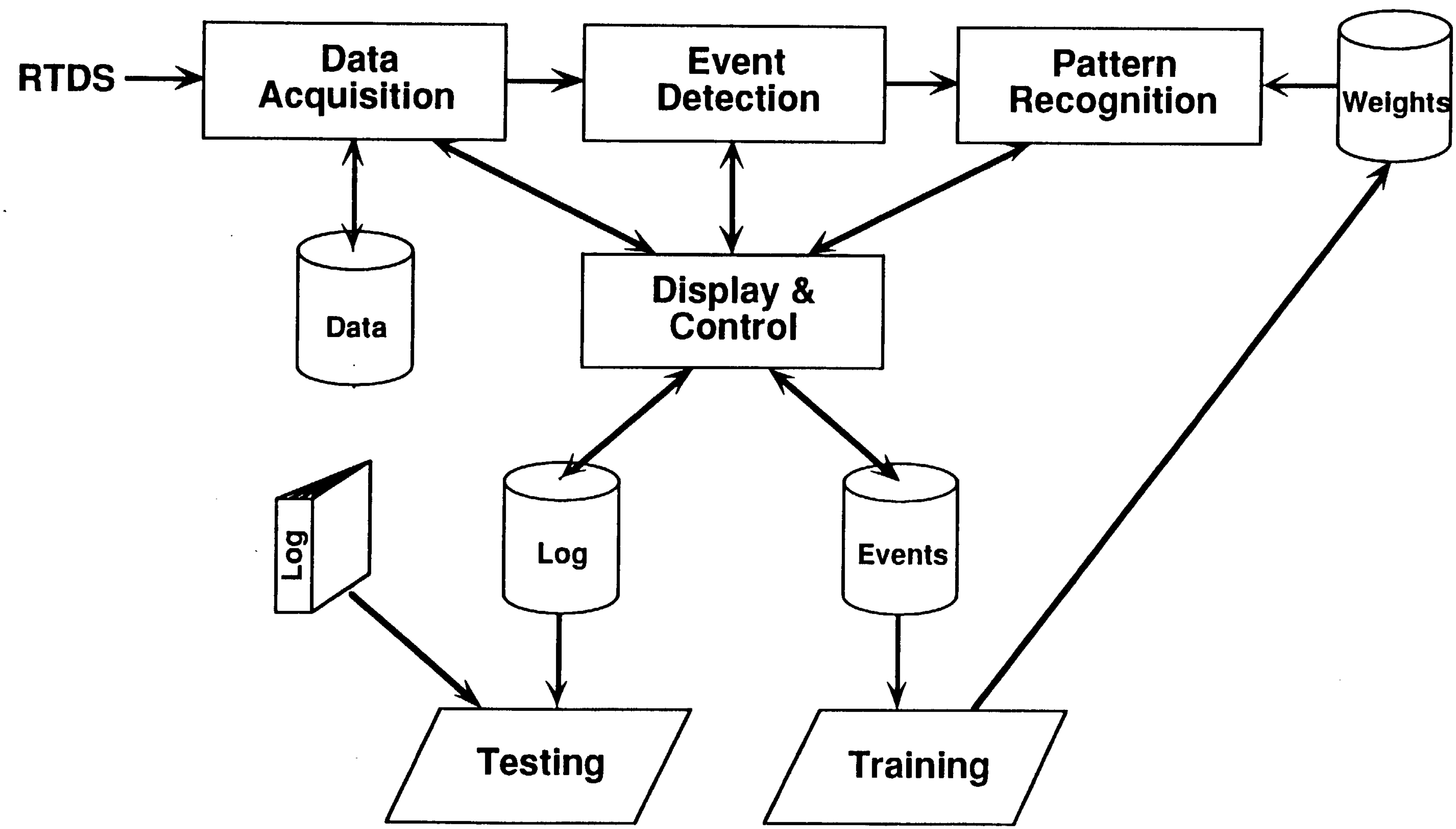
Prototype Architecture



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Accomplishments

- Electrical Motor Identification
  - STS-56 - (early April launch)
    - Demonstrated in RTDS Lab
    - Focused on data acquisition and event detection
    - Pattern recognition via backprop-trained feed-forward neural net
  - STS-55 (late April launch)
    - Demonstrated in Mission Control
    - Pattern recognition via backprop-trained feed-forward neural net successfully recognized 115 of 139 three phase test signatures and 34 of 43 one phase test signatures
    - Attempted to use linear discriminants; wouldn't train

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Near-Term Plans

- Electrical Motor Identification
  - STS-57 (late May launch): fuzzy logic / Bayesian logic (NASA/Ames); radial basis neural net
  - STS-51 (July launch): Cross-correlation; inductive reasoning
- Guidance, Navigation, and Control
  - STS-51 (July launch): Initial demonstration

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General Purpose Tool

- Talk title: “A Pattern Recognition Toolkit for Time Series Signature Analysis”
  - => general purpose toolkit rather than individual applications
  - Learning by doing
- General purpose pattern recognition application infeasible
  - Pattern recognition is a very broad topic
  - Many kinds of approaches to pattern recognition problems; no approach is the best for all circumstances
- What is feasible?
  - Set of interconnecting signal analysis and pattern recognition tools
  - Guidelines (maybe even cookbook) for building special-purpose strip chart chart pattern recognition applications

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Analysis of Stochastic Time Series Data

Jeffrey Scargle
Ames Research Center

Many astronomical objects are variable in brightness (variable stars, active galactic nuclei, quasars, radio galaxies, galactic X-ray sources, etc.). In some cases the variability is periodic, but in the vast majority of those listed the variations are disordered and unpredictable. (Note: We are here discussing real variations in source brightness, not observational errors. Unfortunately astronomers use the term "noise" to refer to stochastic variation, even when it is intrinsic to the source.)

The goal of this work is to understand the physical processes underlying the observed stochastic variations. As with most data analysis, this is carried out by developing models of the processes and comparing the model behavior with that of the time series data for the astronomical objects.

To this end we have developed two classes of analysis tools:

(1) models to represent stochastic physical processes:

(a) random processes
(b) chaotic processes (chaotic dynamical systems)

(2) data analysis tools:

(a) deconvolution methods
(b) wavelet analysis; the scalegram
(c) methods for unevenly spaced data
(d) nonlinear prediction; Lyapunov exponent estimation

We present a case study in which wavelet methods were used to analyze a long time series for the extremely active fluctuations of the X-ray source Scorpius X-1. The self-similar behavior detected by the use of the scalegram (a wavelet-analog of the power spectrum) led us to consider a class of spatially extended models called coupled map lattices (related to cellular automata). A particular model, called the "dripping handrail," was singled out because it represents physical processes operating in the accretion disks thought to be present in the astronomical objects.

The power spectra and scalegrams of time series synthesized with this model agree very well with those of the observed time series data. In particular, both show two features characteristic of the variability of a class of x-ray sources including Scorpius X-1: quasi-periodic oscillations (QPO's) and low-frequency noise (LFN). These features were previously thought to be due to two separate mechanisms, but we argue that they are due to a single physical process.

Bibliography:

Scargle, J. Studies in astronomical time series analysis.
I: Modeling random processes in the time domain.

Astrophysical Journal Supplements, 1981, 45, 1-71.

------ II: Modeling chaotic and random processes with linear filters. Astrophysical Journal, 1982, 263, 835

------ III: Fourier transforms, autocorrelation functions, and cross-correlation functions of unevenly spaced data, Astrophysical Journal, 343, 874

------ IV: Modeling chaotic and random processes with linear filters. Astrophysical Journal, 359, 469-482

Donoho, D., and Scargle, J. (1993) Studies in astronomical time series analysis. V: Wavelets and the scalegram; preprint.

Scargle, J., Donoho, D., Crutchfield, J., Steiman-Cameron, T., Imamura, J., and Young, K. (1993), The Quasi-Periodic Oscillations and Low-Frequency Noise of Scorpius X-1 as Transient Chaos: A Dripping Handrail?; preprint.

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ANALYSIS OF STOCHASTIC TIME SERIES DATA

- THE NATURE OF STOCHASTIC VARIATIONS
  RANDOMNESS VS. CHAOS

- TIME SERIES ANALYSIS METHODS

  MODELS: AUTOREGRESSIVE (AR)
  MOVING AVERAGE (MA)
  CHAOS MODELS

  DECONVOLUTION TO ESTIMATE MODEL PARAMETERS

  CHAOS: DIMENSION, LYAPUNOV EXPONENTS

  WAVELET METHODS
  DIAGNOSE SELF-SIMILARITY, 1/f NOISE
  IDEAL SMOOTHING
  IMAGE PROCESSING
  DATA COMPRESSION

- A CASE STUDY: SCORPIUS X-1, A DRIPPING HANDRAIL

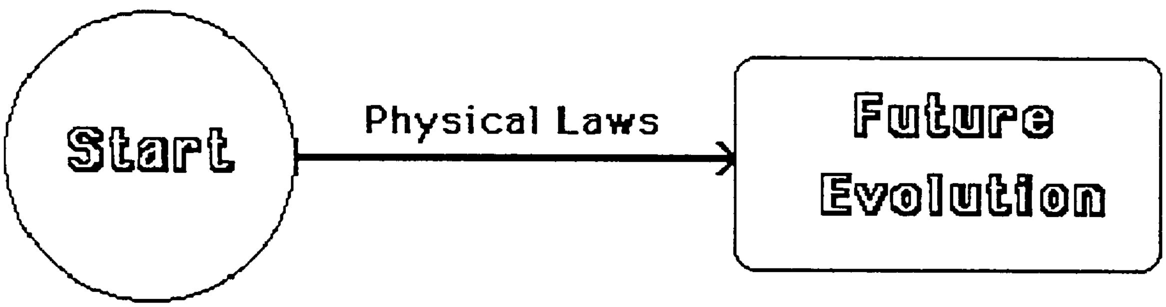
WHAT IS CHAOS?

Evolution of a Chaotic System Has these Properties:

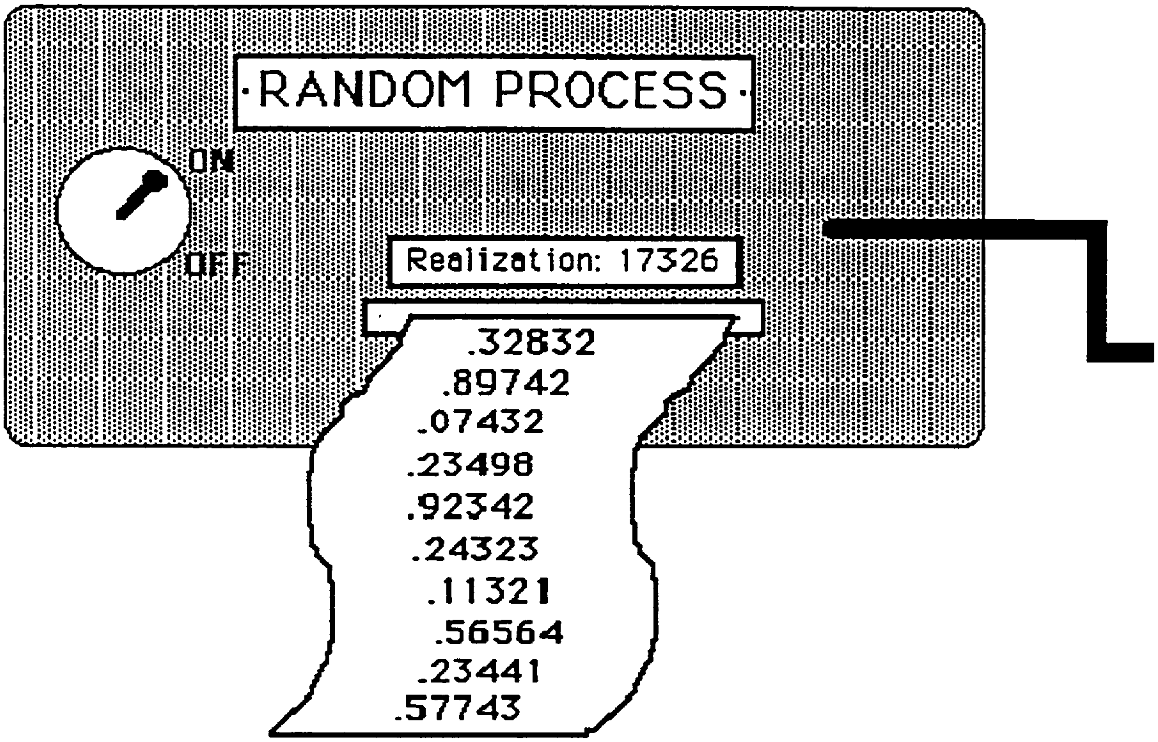
- **DISORDER**: The evolution of the system appears irregular and unpredictable.

- **DETERMINISM**: if initial conditions are EXACTLY the same, the future evolution is the same.

- **SENSITIVITY TO INITIAL CONDITIONS** : If initial conditions are even A TINY BIT different, the future evolution is very different (exponential divergence).



Even simple systems can be chaotic!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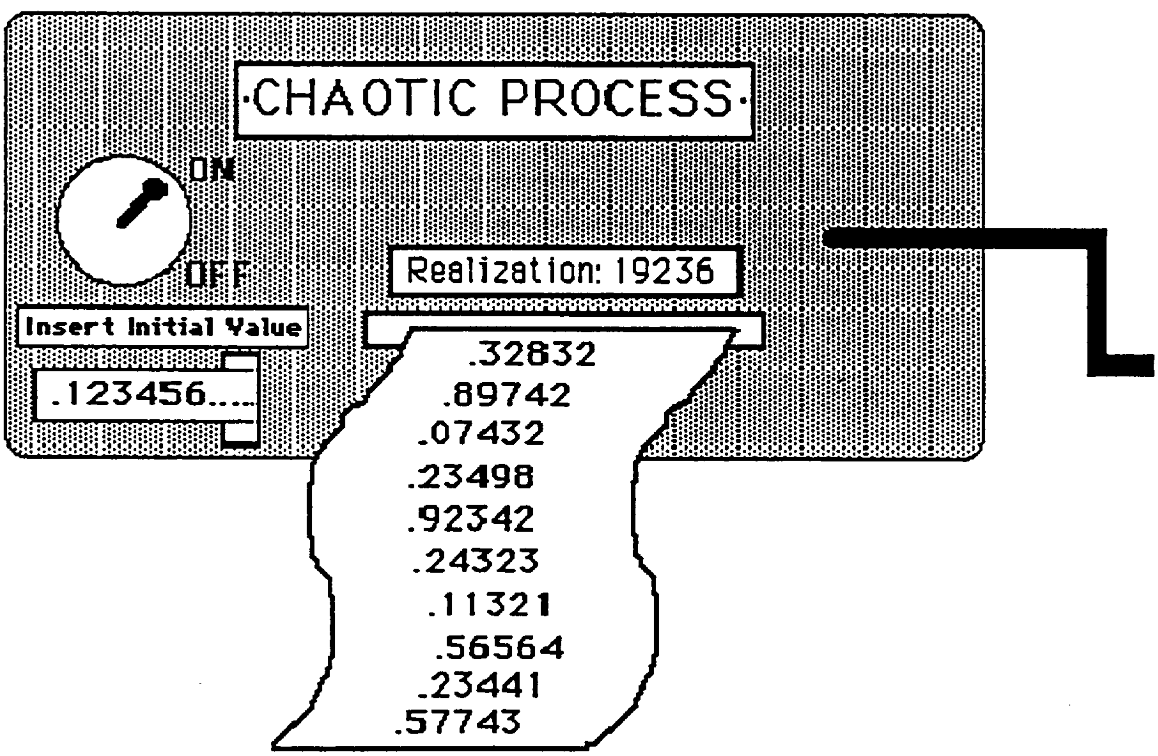
ON
OFF
Realization: 17326
.32832
.89742
.07432
.23498
.92342
.24323
.11321
.56564
.23441
.57743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OFF
Realization: 19236
Insert Initial Value
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.89742
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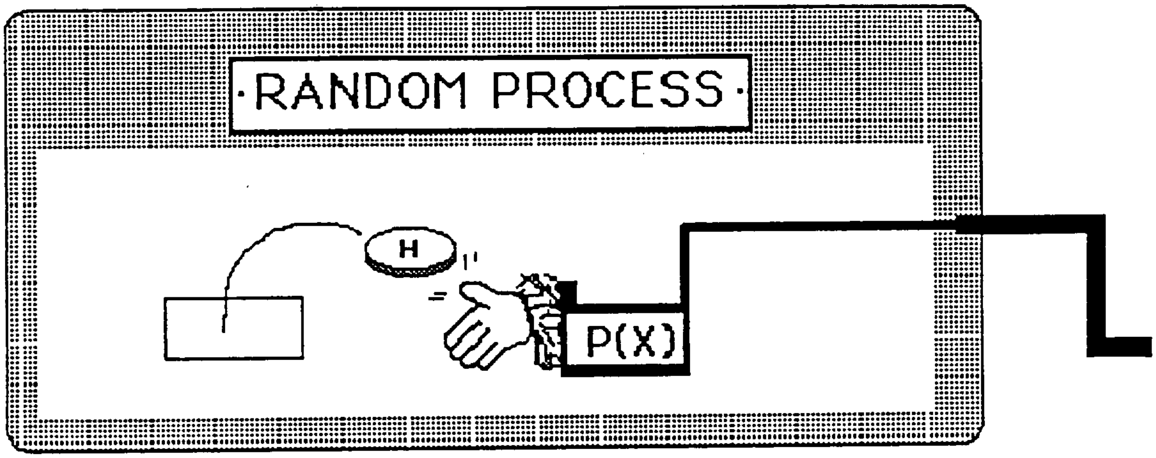
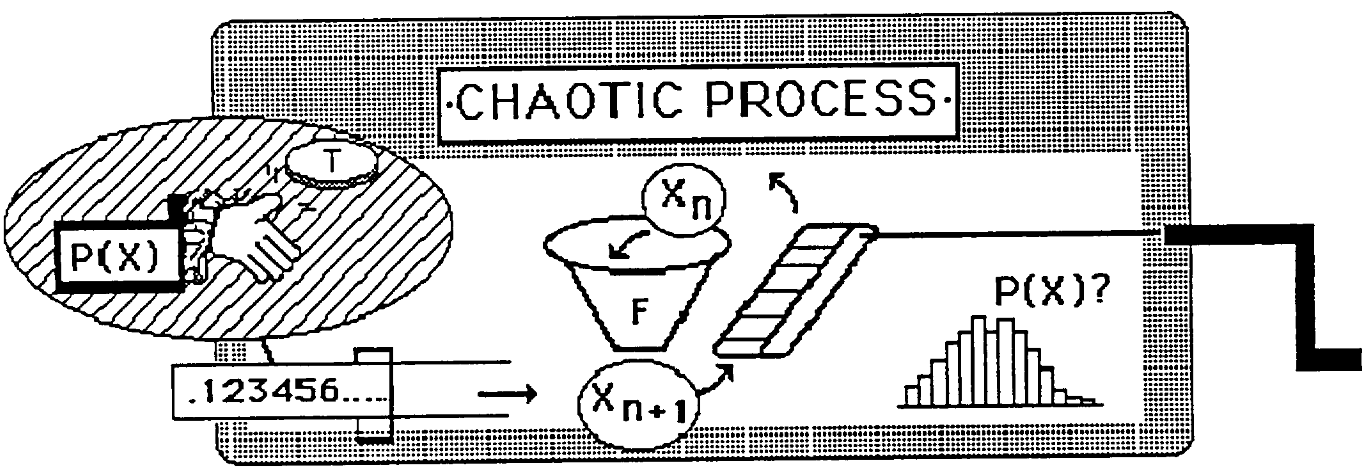

·RANDOM PROCESS·
H
P(X)


·CHAOTIC PROCESS·
T
P(X)
X_n
F
X_{n+1}
.123456.....
P(X)?

The Bernoulli Shift

(a) One-sided: $X_{n+1} = (2X_n) \bmod 1$

Initial value: $X_0 = .b_1 b_2 b_3 b_4 b_5 \ldots b_N$

$\Longrightarrow$ $X_1 = .b_2 b_3 b_4 b_5 \ldots b_N$

$X_2 = .b_3 b_4 b_5 \ldots b_N$

$X_3 = .b_4 b_5 \ldots b_N$

$\vdots$

$X_N = 0$

(a) Two-sided: $X_0 = \ldots b_{-3} b_{-2} b_{-1} \,.\, b_1 b_2 b_3 \ldots$

$X_1 = \ldots b_{-3} b_{-2} b_{-1} b_1 \,.\, b_2 b_3 \ldots$

$X_2 = \ldots b_{-3} b_{-2} b_{-1} b_1 b_2 \,.\, b_3 \ldots$

$\vdots$

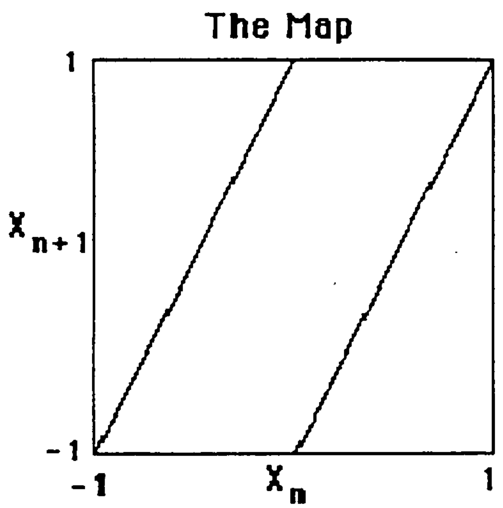
$X_{-1} = \ldots b_{-3} b_{-2} \,.\, b_{-1} b_1 b_2 b_3 b_4 b_5 \ldots$

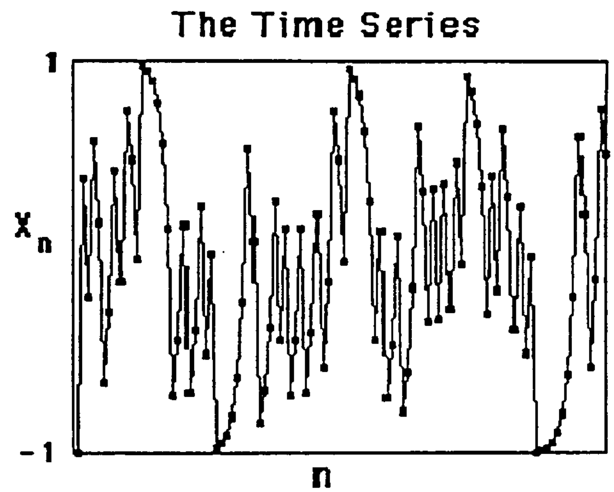
$X_{-2} = \ldots b_{-3} \,.\, b_{-2} b_{-1} b_1 b_2 b_3 b_4 b_5 \ldots$

$\vdots$

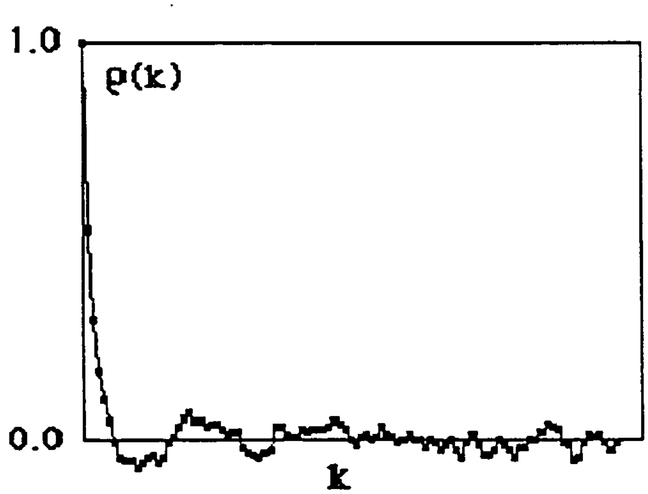
(The World's most random process!)

Modified map: $X_{n+1} = 2X_n - \mathrm{Sign}(X_n) \quad -1 \le X_n \le 1$





Probability distribution:	$P(X)$	=	1/2	$-1 \le X_n \le 1$
			0	otherwise
Mean value:	$E(X)$	=	0	
Variance:	σ^2	=	1/3	
Autocorrelation:	$\rho_X(k)$	=	$1/3\,(1/2)^k$	$k=0, 1, 2, \ldots$



THE LOGISTIC EQUATION:

$$X_{n+1} = R X_n (1 - X_n)$$

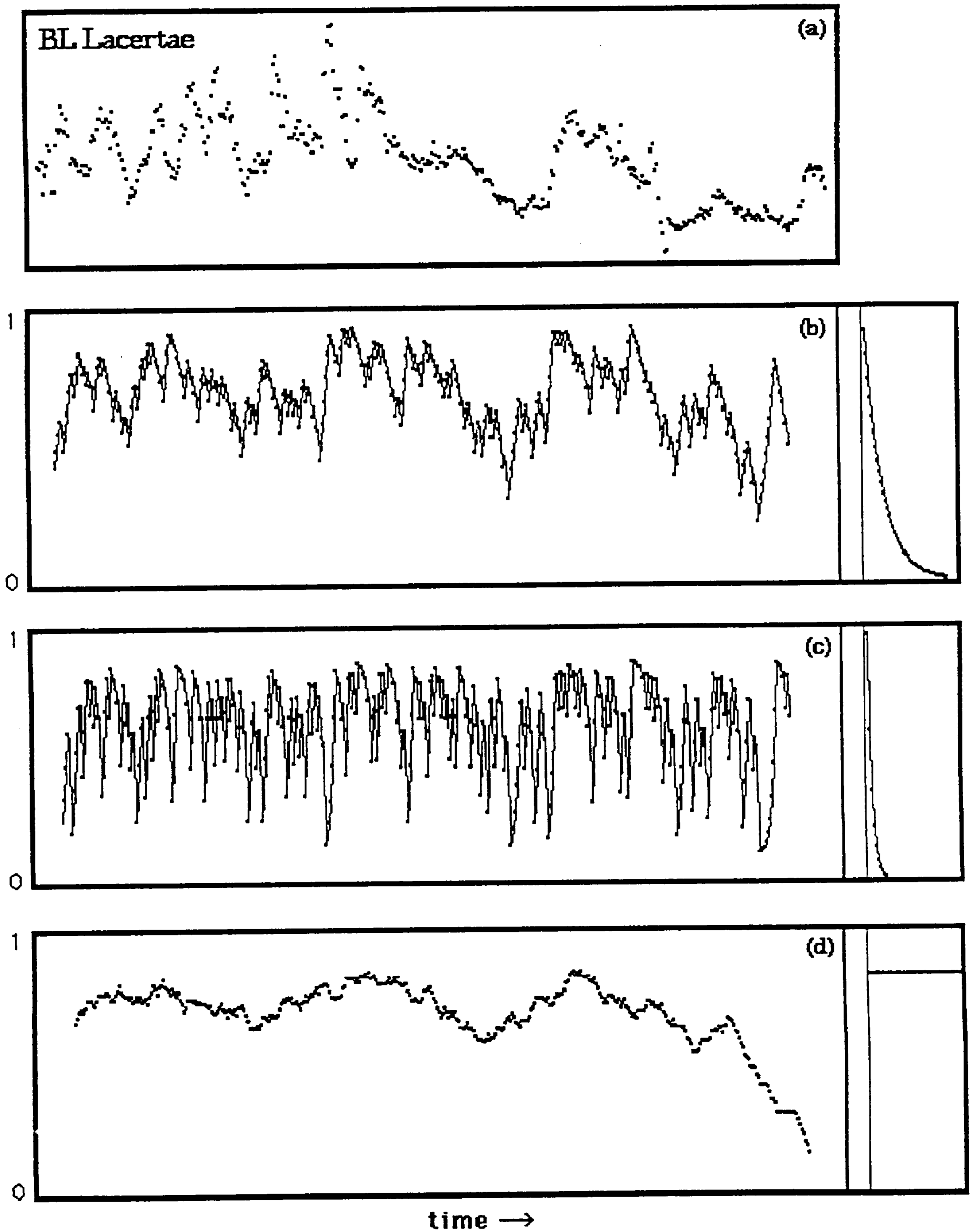


Figure 1

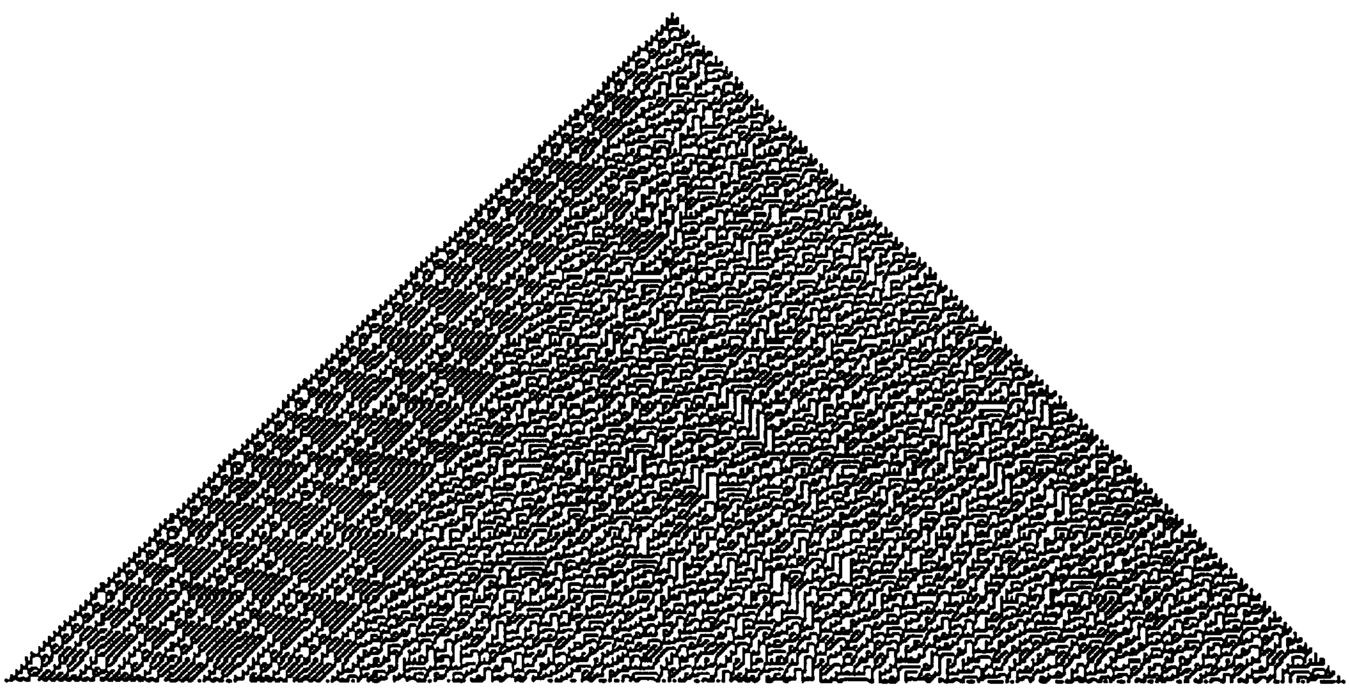
Cellular Automaton Process

Discrete states: $Y_{n,m} = 0 \text{ or } 1$

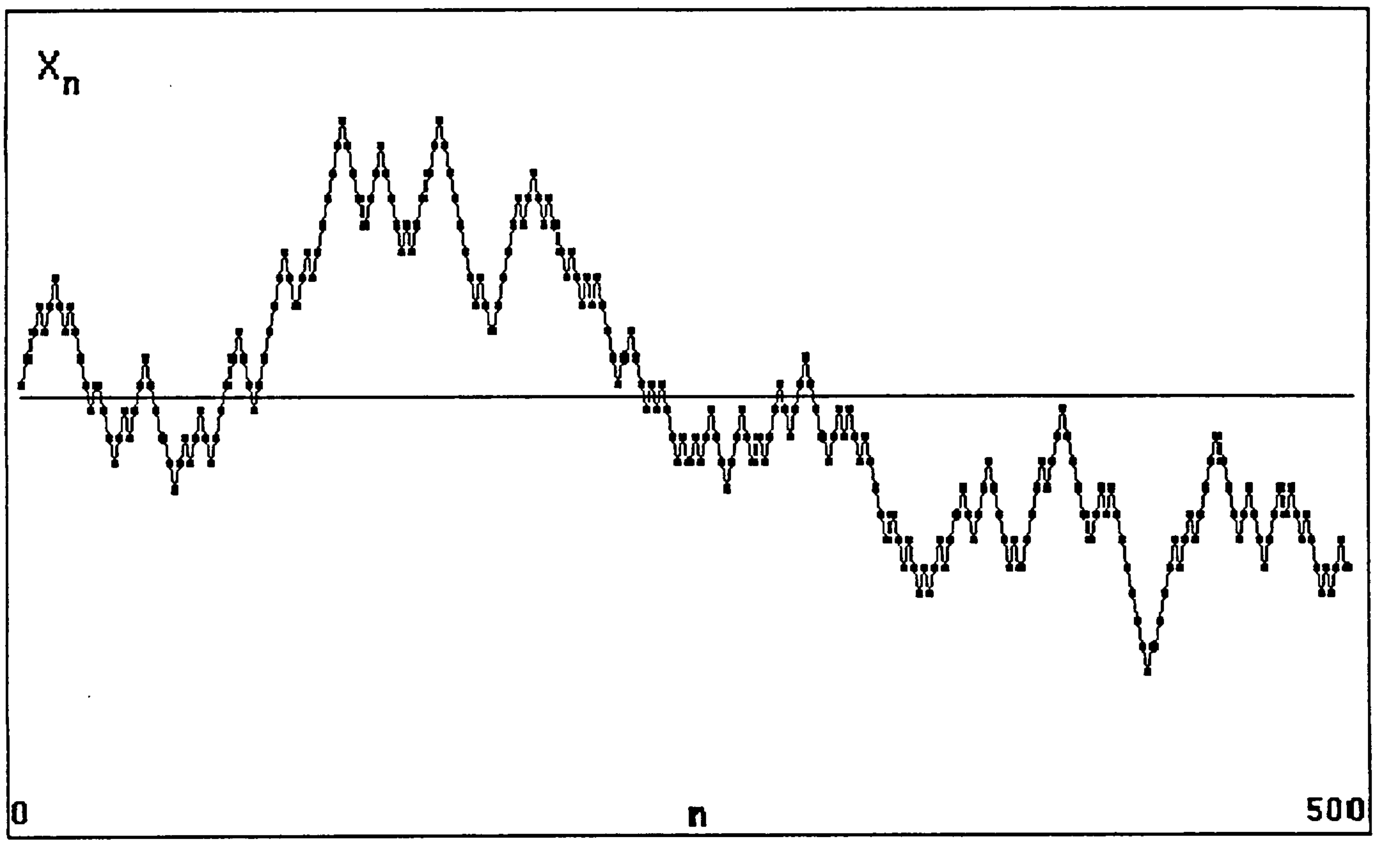
Dynamics: $Y_{n+1,m} = [Y_{n,m-1} + D(Y_{n,m}, Y_{n,m+1})] \bmod 2$

$$D(x,y) = \begin{cases} 0 & x=1,\ y=1 \\ 1 & \text{otherwise} \end{cases}$$

Initial state: $Y_{0,0} = 1, Y_{0,m} = 0$



Time Series: $$X_n = \sum_{k=0}^{n} (Y_{k,0} - .5)$$



Autoregressive model: $R = A*X$; $A = C^{-1}$

$$A = (\ldots, A_{-3}, A_{-2}, A_{-1}, \mathbb{1}, A_1, A_2, A_3, \ldots)$$

$$R_n = X_n + A_1 X_{n-1} + A_2 X_{n-2} + \ldots \text{ (causal)}$$

$$R_n = X_n + A_{-1} X_{n+1} + A_{-2} X_{n+2} + \ldots \text{ (acausal)}$$

$$R_n = \ldots A_{-1} X_{n+1} + X_n + A_1 X_{n-1} + \ldots \text{ (mixed)}$$

Example: $A = (\mathbb{1}, A_1) = (\mathbb{1}, -a)$

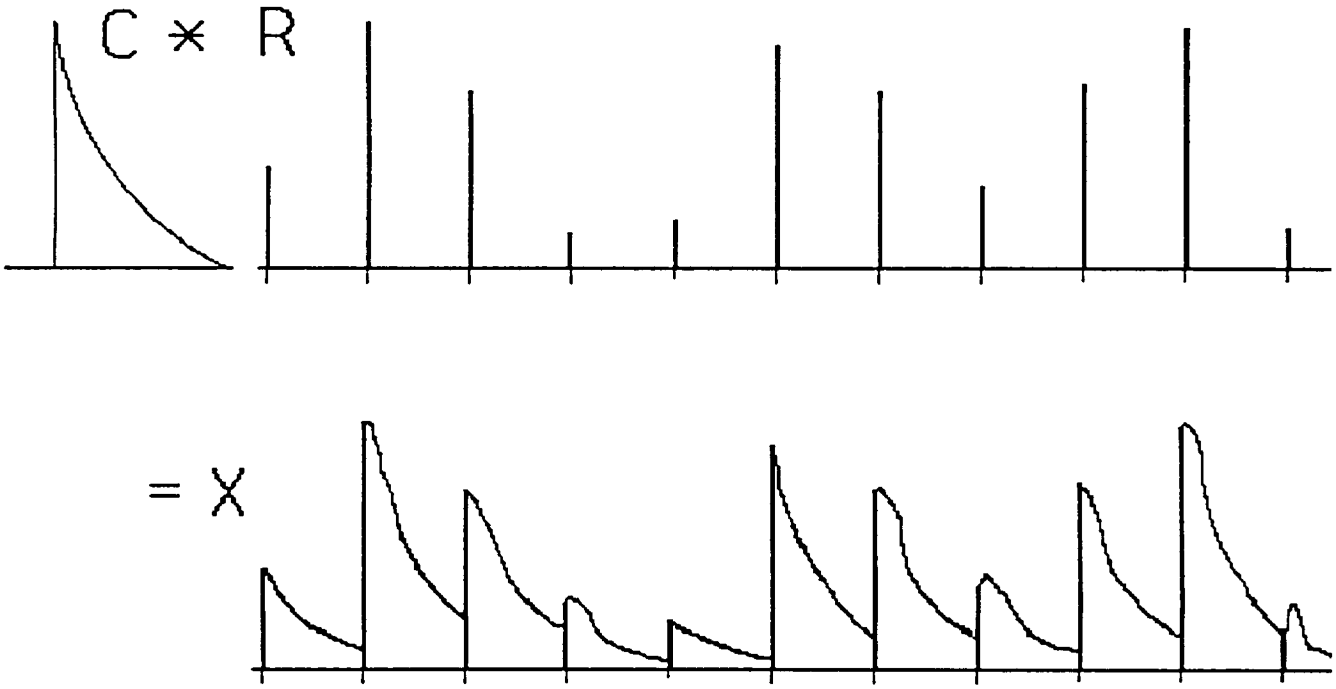
$$R_n = X_n - aX_{n-1}$$

$$C = (1, a, a^2, a^3, a^4 \ldots)$$

$$X_n = R_n + aR_{n-1} + a^2 R_{n-2} + a^3 R_{n-3} \ldots$$

Moving average model: $X = C * R$

$$X_n = \sum_k C_k R_{n-k} \quad \text{(causal <--> } k>0\text{; acausal <--> } k<0\text{)}$$

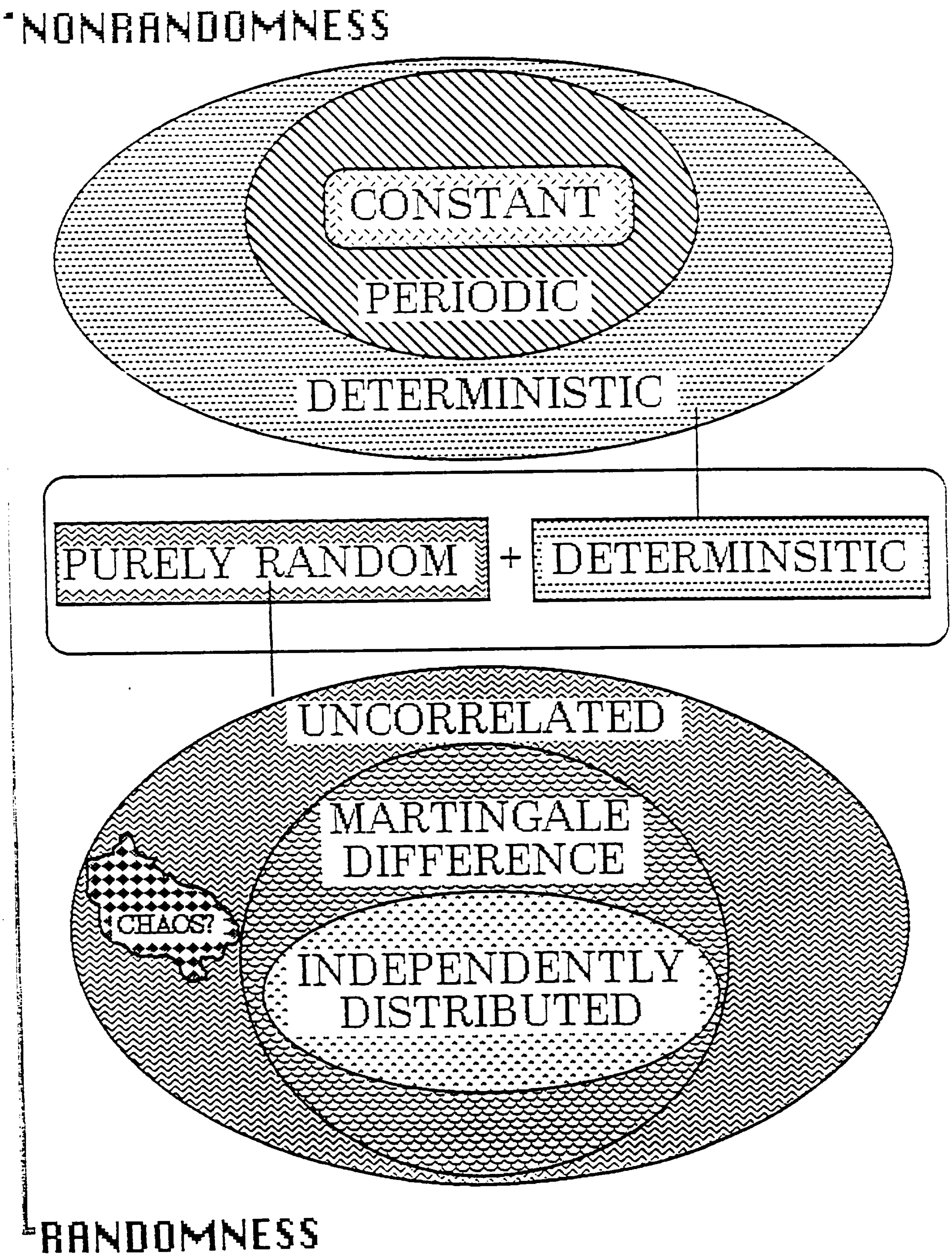


WOLD DECOMPOSITION THEOREM

Let X be any stationary process; then

$$X = C * R + D$$

- R is a WHITE noise process (the innovation)
- C is a causal filter ($C_i=0$, $i<0$, i.e. no output before input)
- D is a linearly deterministic process (future is linearly predictable from past with zero mean-square-error)
- R, D stationary, not correlated with each other
- C is minimum delay


NONRANDOMNESS
CONSTANT
PERIODIC
DETERMINISTIC
PURELY RANDOM
+
DETERMINSITIC
UNCORRELATED
MARTINGALE
DIFFERENCE
CHAOS?
INDEPENDENTLY
DISTRIBUTED
RANDOMNESS

DECONVOLUTION TECHNIQUE:

THE DATA: Y_n , $n = 0, 1, 2, \ldots, N$

RANDOM PROCESS

THE MODEL: $Y = R * C$ (convolution)

R is purely random
C is a constant pulse shape

Note that if $A = C^{-1}$ then convolving A into Y gives R.

So define $R = A * Y$ and maximize its randomness.

CHAOTIC PROCESS

THE MODEL: $Y = R * C$ (convolution)

R is purely chaotic
C is a constant pulse shape

Note that if $A = C^{-1}$ then convolving A into Y gives R.

So define $R = A * Y$ and maximize its . . . chaosity.

The Fundamental Problem:

- Given time series data $\{X_n, n = 1, N\}$
- Estimate: the filter C
  the chaotic innovation R
  the recurrence function F ; $R_{n+1} = F(R_n, \ldots)$

The Solution:

Seek the filter $A = (A_{-q}, \ldots, A_{-2}, A_{-1}, \mathbb{1}, A_1, A_2, \ldots, A_p)$ which makes $X = A * Y$ maximally chaotic by minimizing H; A is then an estimate of the inverse of C; F derived by plotting R_{n+1} vs. R_n, etc.

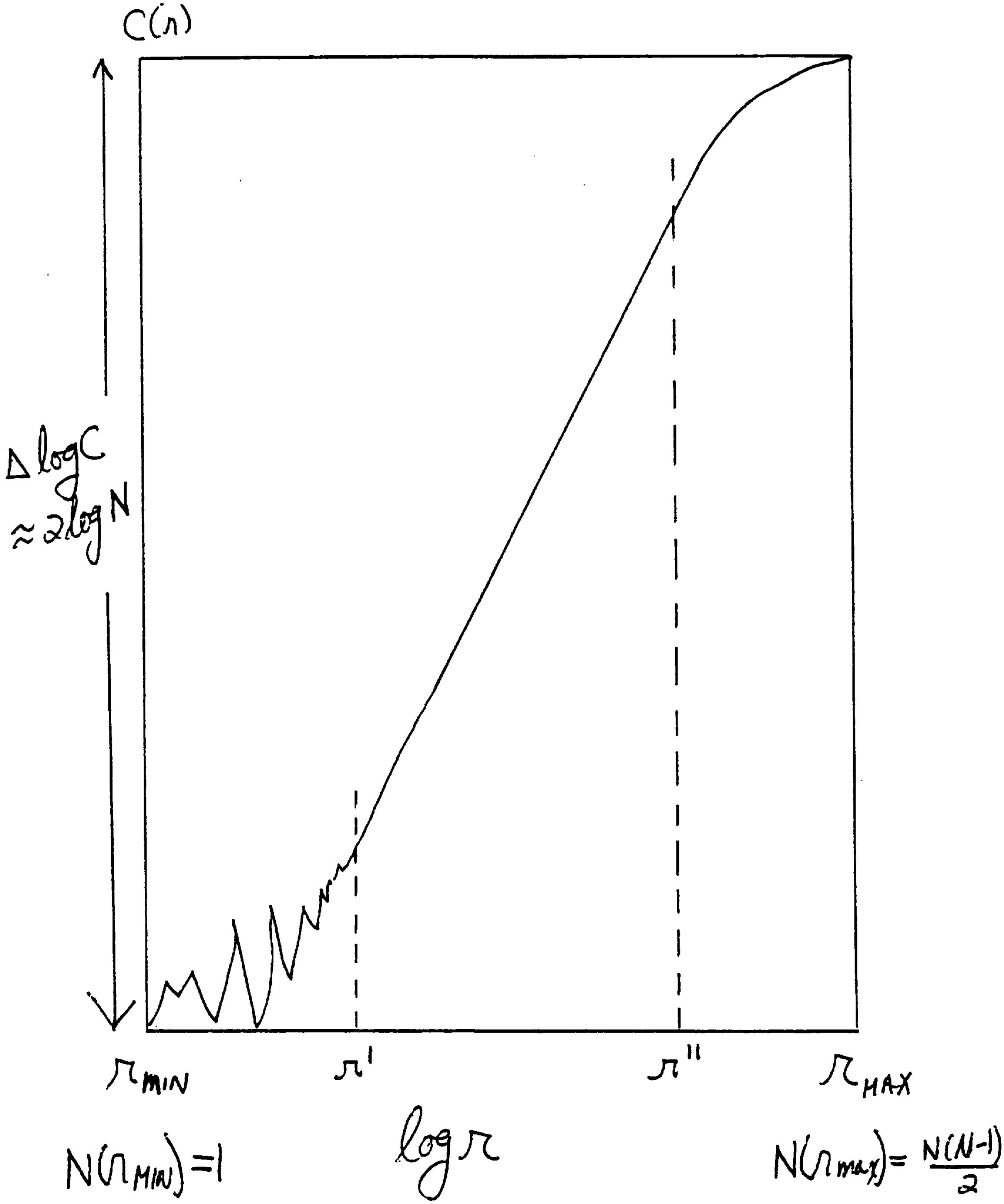
Penalty Function $H(X)$:

Given a set of data points $\{X_n = 1, 2, \ldots, N\}$:

- Construct a grid of $(M+1)$-dimensional cells in the phase space $(X_{n+1}, X_n, X_{n-1}, \ldots, X_{n-M+1})$
- Plot in this space the **N-M** points derivable from the data
- Then define H as one of the following:

$H^{(1)}$ = Total volume of the cells containing data points

$H^{(2)} = \sum P_i \log P_i$ (P_i ~ number of points in cell i)


C(r)
Δ log C ≈ 2 log N
r_MIN
r'
r''
r_MAX
log r
N(r_MIN) = 1
N(r_max) = N(N-1)/2

RUELLE'S LIMIT

$$\text{SLOPE} = \frac{\log N(r'') - \log N(r')}{\log r'' - \log r'}$$

$$N(r') \geqq 1$$

$$N(r'') \leqq \tfrac{1}{2} N(N-1) < N^2$$

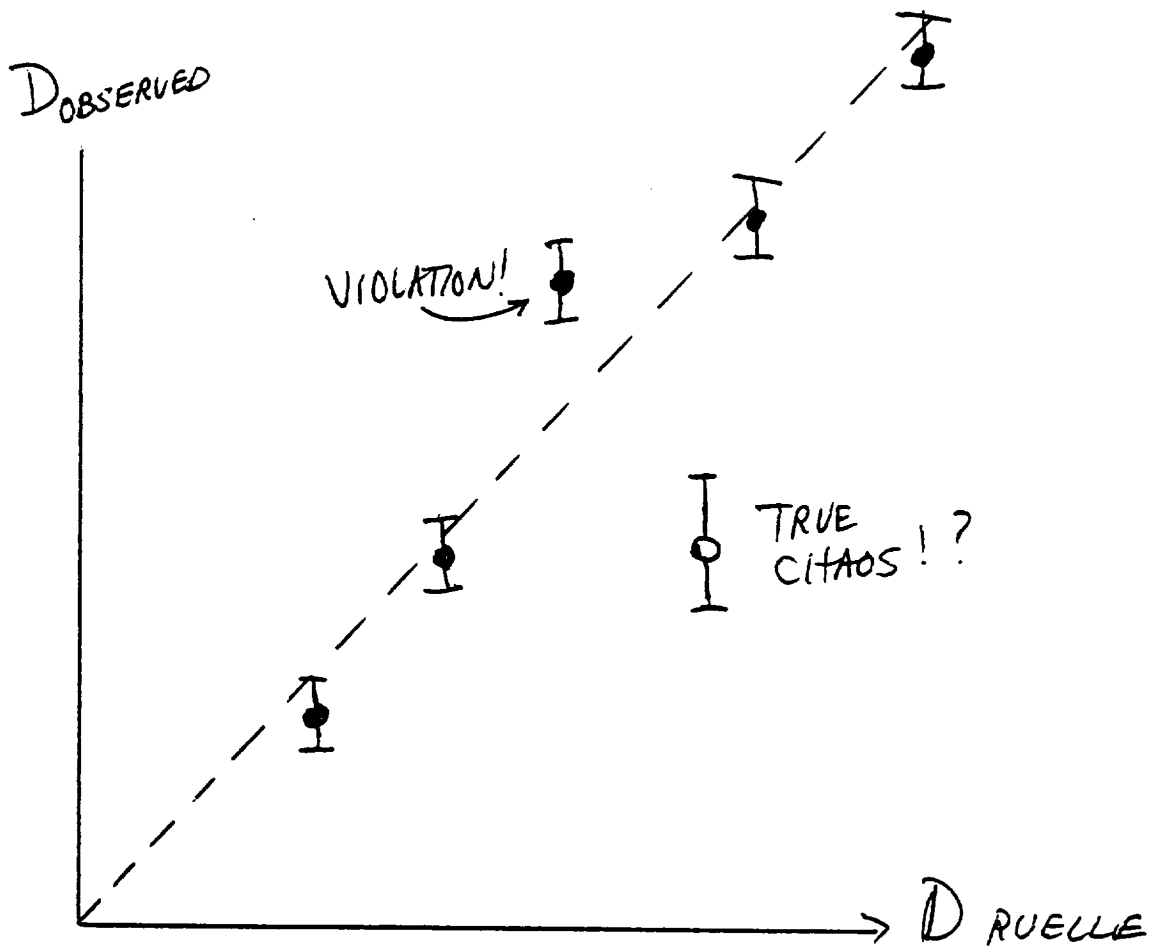
$$\text{SLOPE} \leq \frac{2 \log N}{\Delta \log r}$$

$$\Delta \log r \equiv \log r'' - \log r'$$

TYPICALLY $\Delta \log r \geqq 1$ (ONE DECADE)

SO $\text{SLOPE} \leq 2 \log N$

CONJECTURE



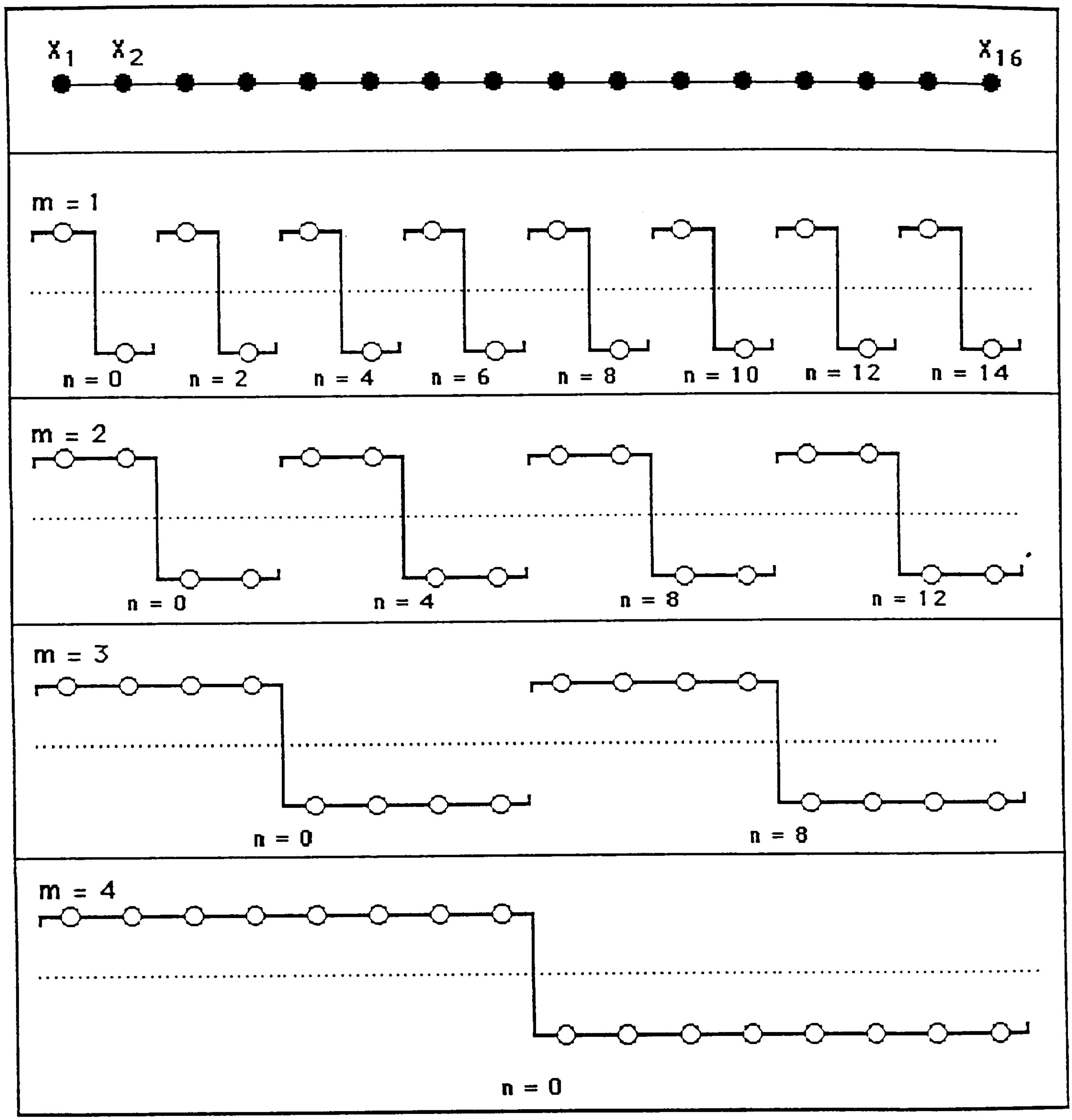
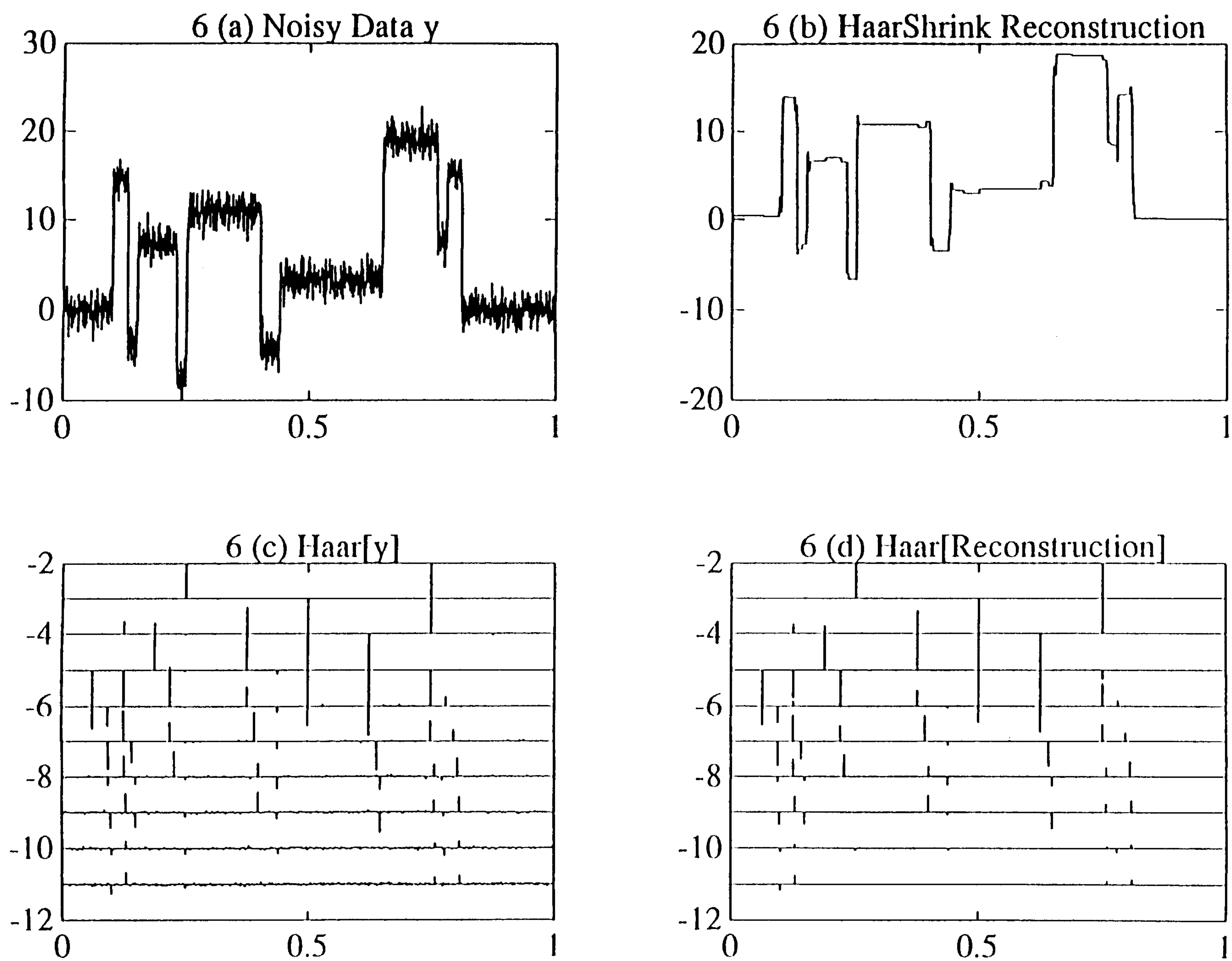


Figure 1: Haar wavelets for time series with 16 samples.
The vertical scale is arbitrary.


6 (a) Noisy Data y
30
20
10
0
-10
0
0.5
1
6 (b) HaarShrink Reconstruction
20
10
0
-10
-20
0
0.5
1
6 (c) Haar[y]
-2
-4
-6
-8
-10
-12
0
0.5
1
6 (d) Haar[Reconstruction]
-2
-4
-6
-8
-10
-12
0
0.5
1

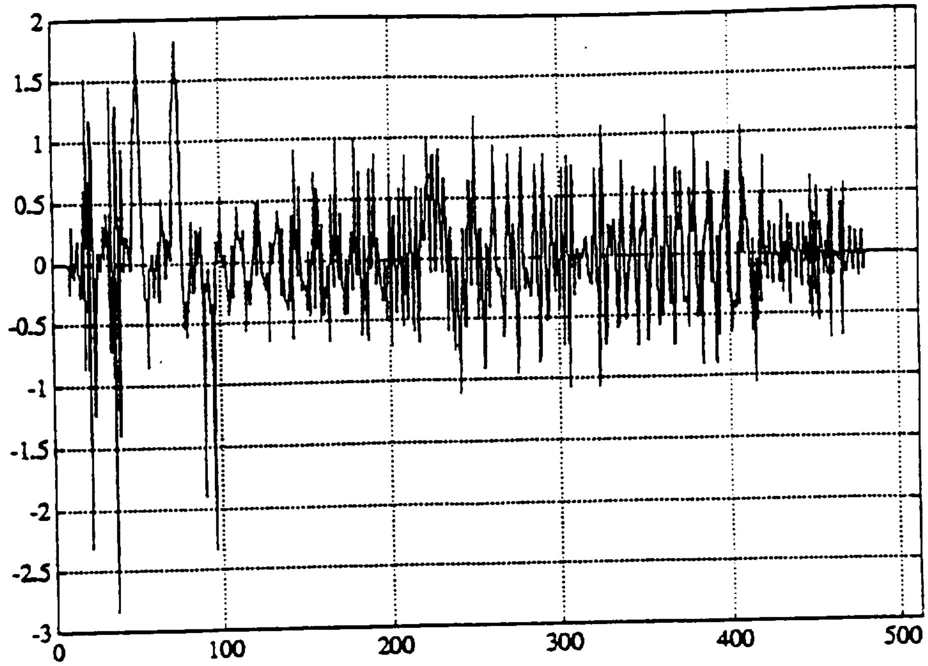


Figure 1: Signal of 512 samples built by adding chirps, truncated sinusoidal waves and waveforms of different time-frequency localizations.

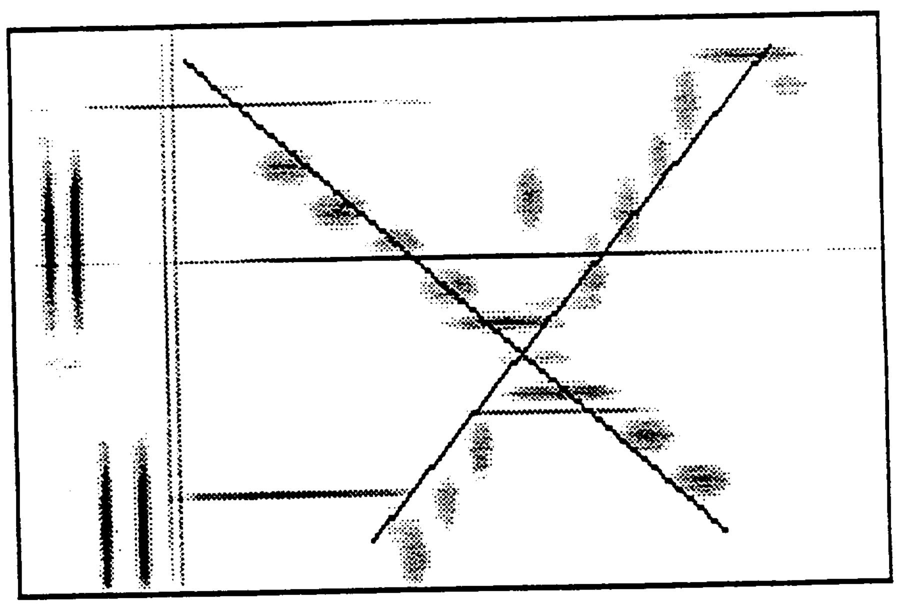


Figure 2: Time-frequency energy distribution $Ef(t,\omega)$ of the signal shown in Fig. 1. The horizontal axis is time. The vertical axis is frequency. The highest frequencies are at the top. The darkness of this time-frequency image increases with the value $Ef(t,\omega)$. The two straight lines are the time-frequency trajectories of the chirps detected from the Gabor time-frequency atoms.

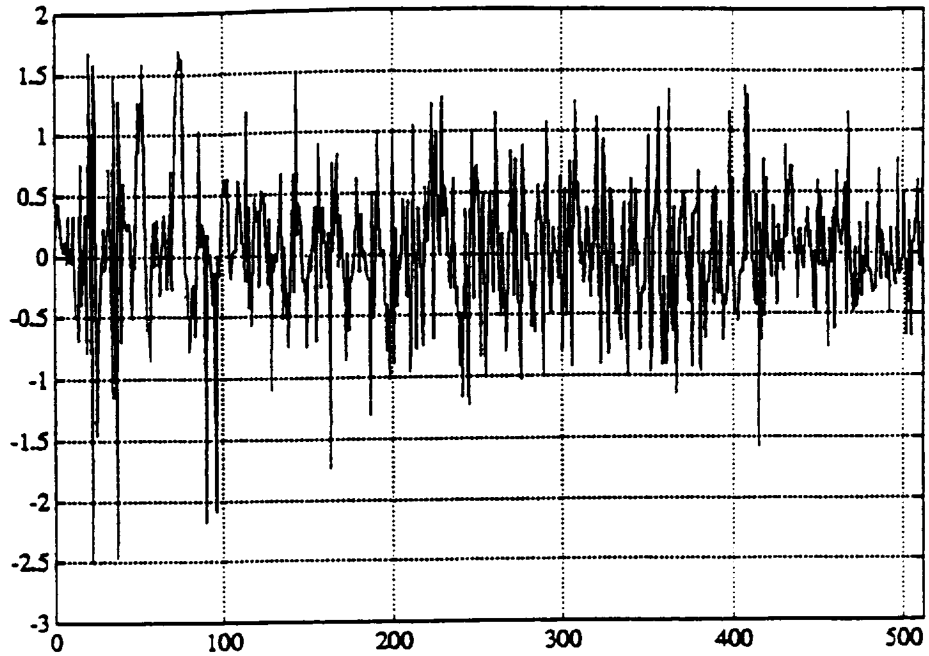


Figure 3: Signal obtained by adding a Gaussian white noise to the signal shown if Fig. 1. The signal to noise ratio is 4 db.

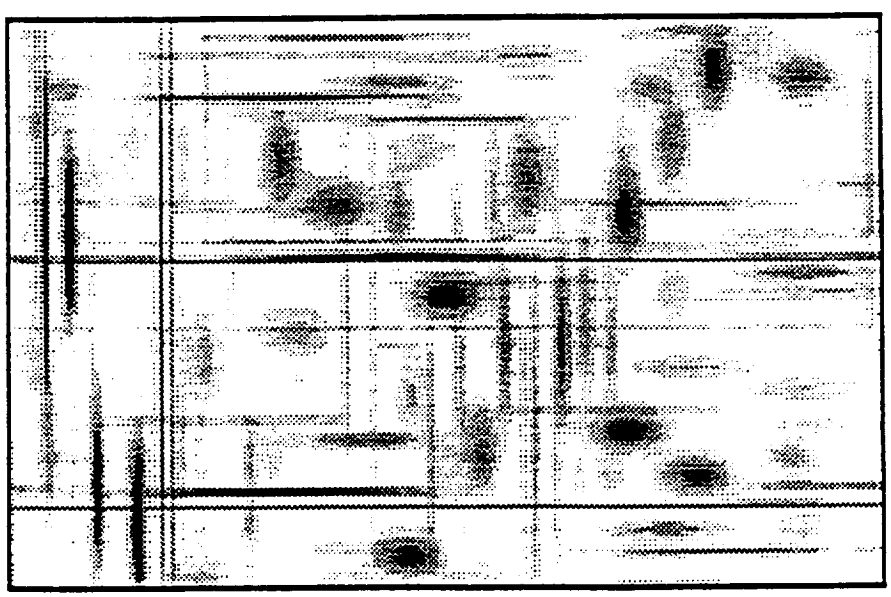


Figure 4: Time-frequency energy distribution of the noisy signal shown in Fig. 4. The white noise component has an energy that is spread across the whole time-frequency plane.

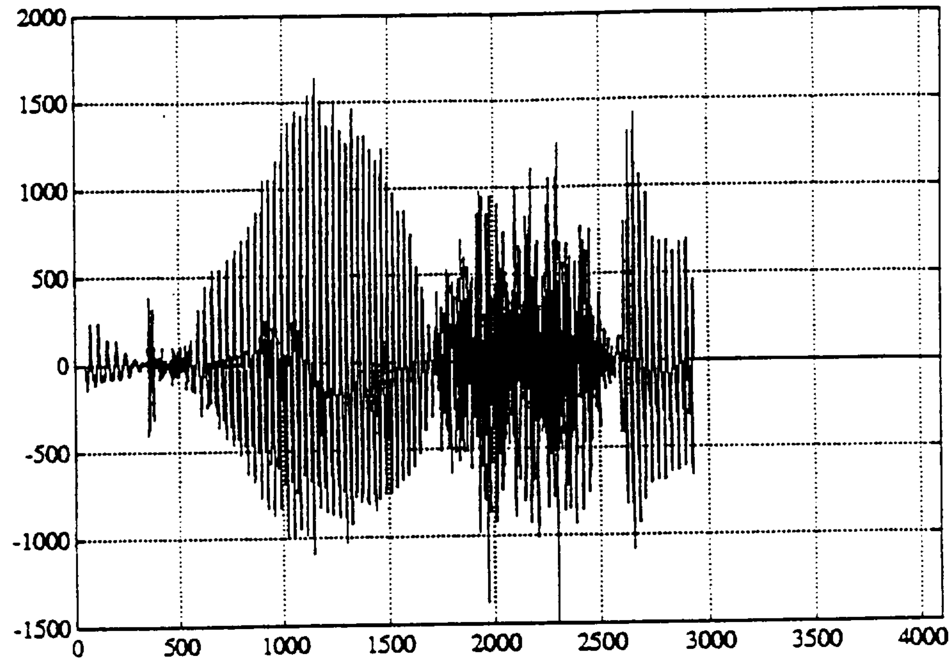


Figure 5: Speech recording of the word "greasy", sampled at 8 kHz.

Figure 6: Time-frequency energy distribution of the speech recording shown in Fig. 5. We see the low-frequency component of the "g", the quick burst transition to the "ea" and the harmonics of the "ea". The "s" has an energy distribution that is similar to a white noise.

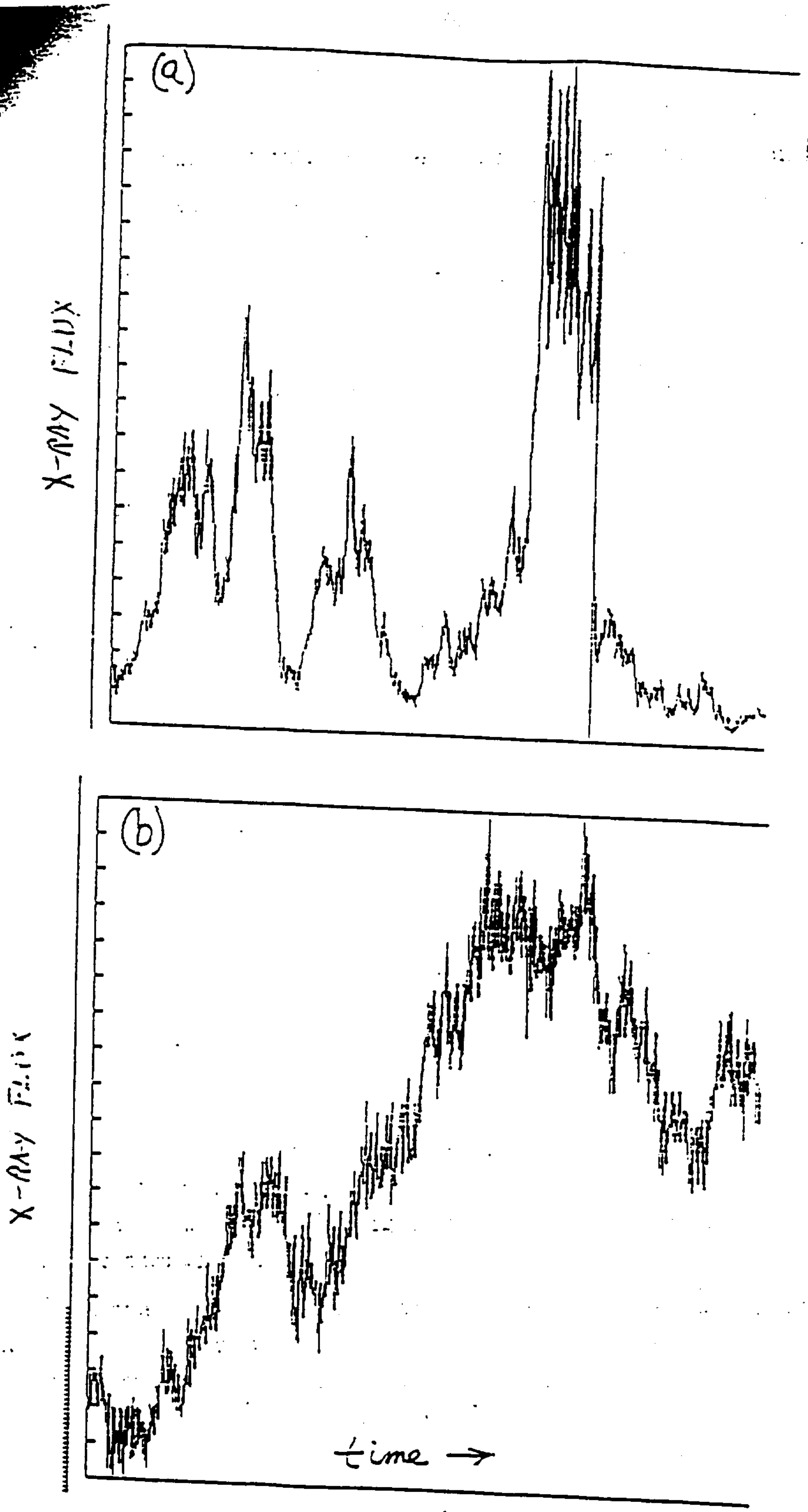
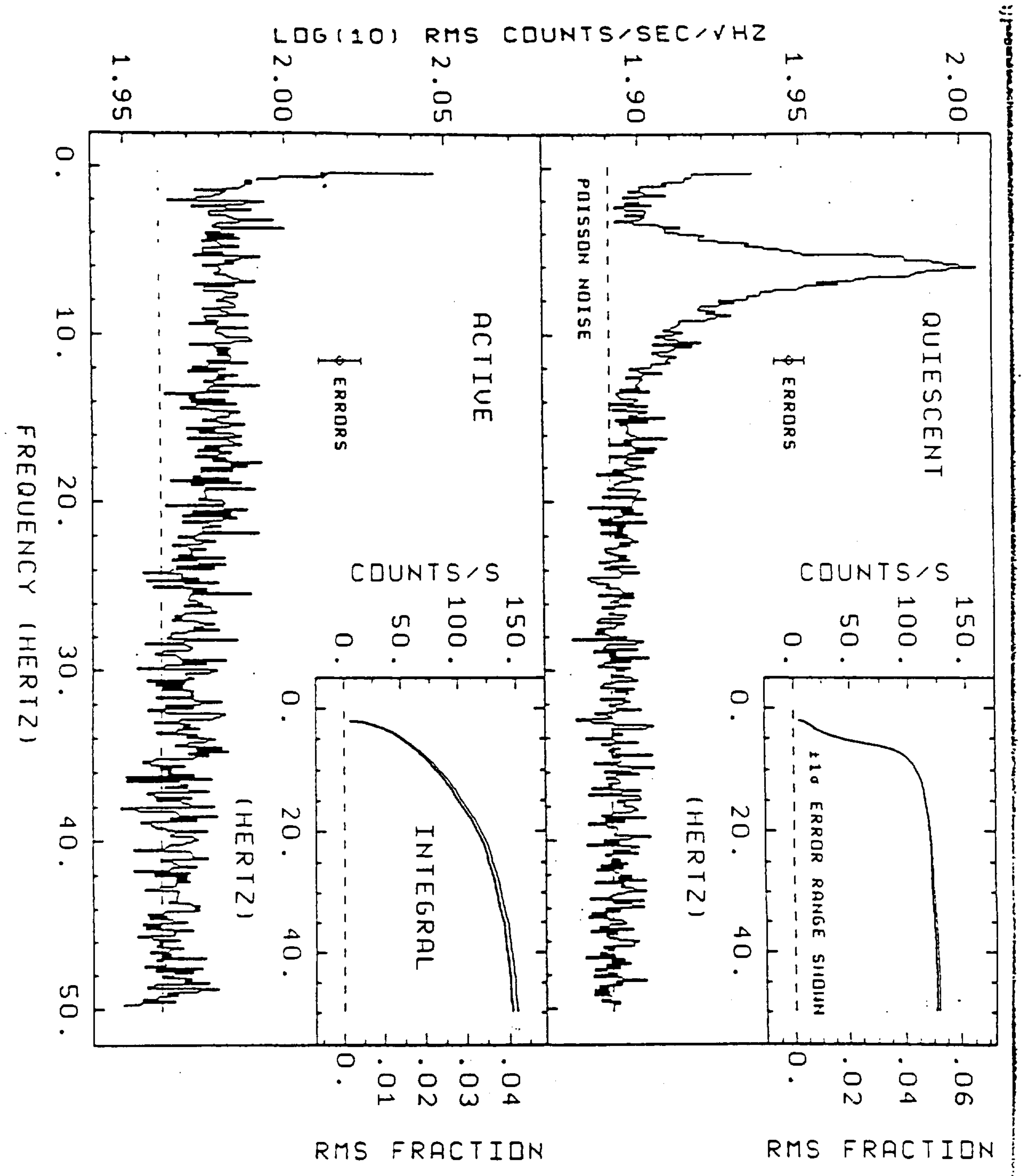
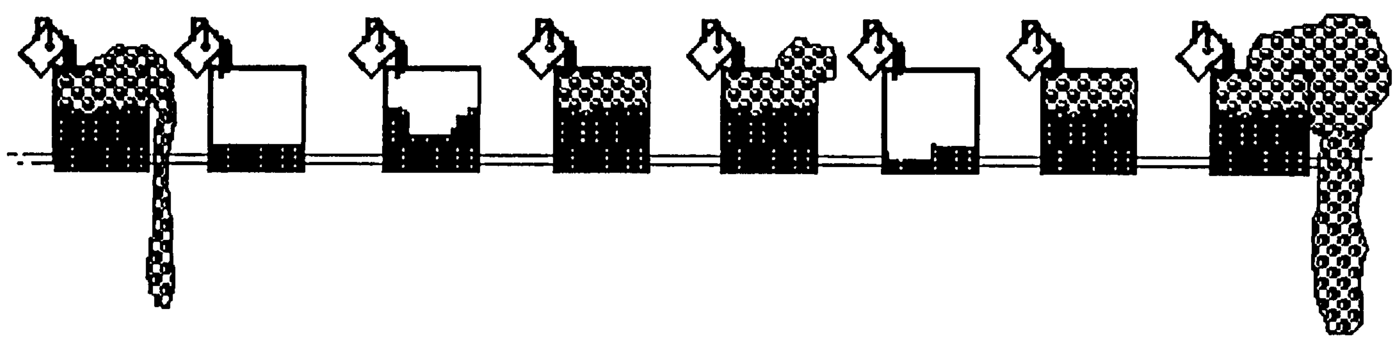


Figure 1: EXOSAT data: X-ray luminosity of Sco X-1 as a function of time. (a) The active period of 25 February 1985 (about 2 hours of data); (b) An expanded and less smoothed segment somewhere in the same interval; we intentionally do not specify what subinterval of (a) is plotted in (b) to emphasize the self-similarity.

2a


LOG(10) RMS COUNTS/SEC/√HZ
QUIESCENT
ACTIVE
ERRORS
ERRORS
POISSON NOISE
COUNTS/S
COUNTS/S
(HERTZ)
(HERTZ)
±1σ ERROR RANGE SHOWN
INTEGRAL
RMS FRACTION
RMS FRACTION
FREQUENCY (HERTZ)

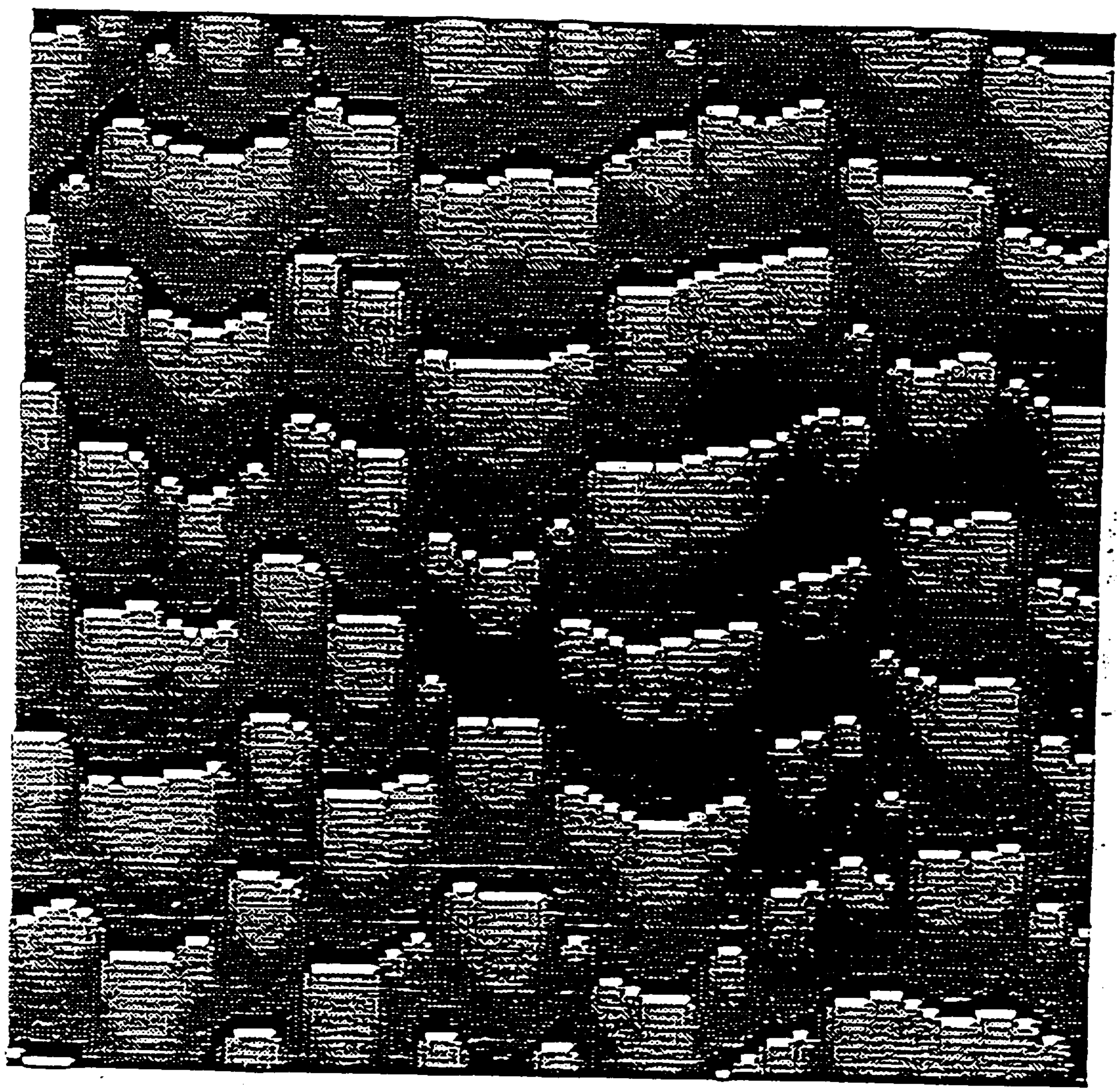
The Dripping Handrail



5948

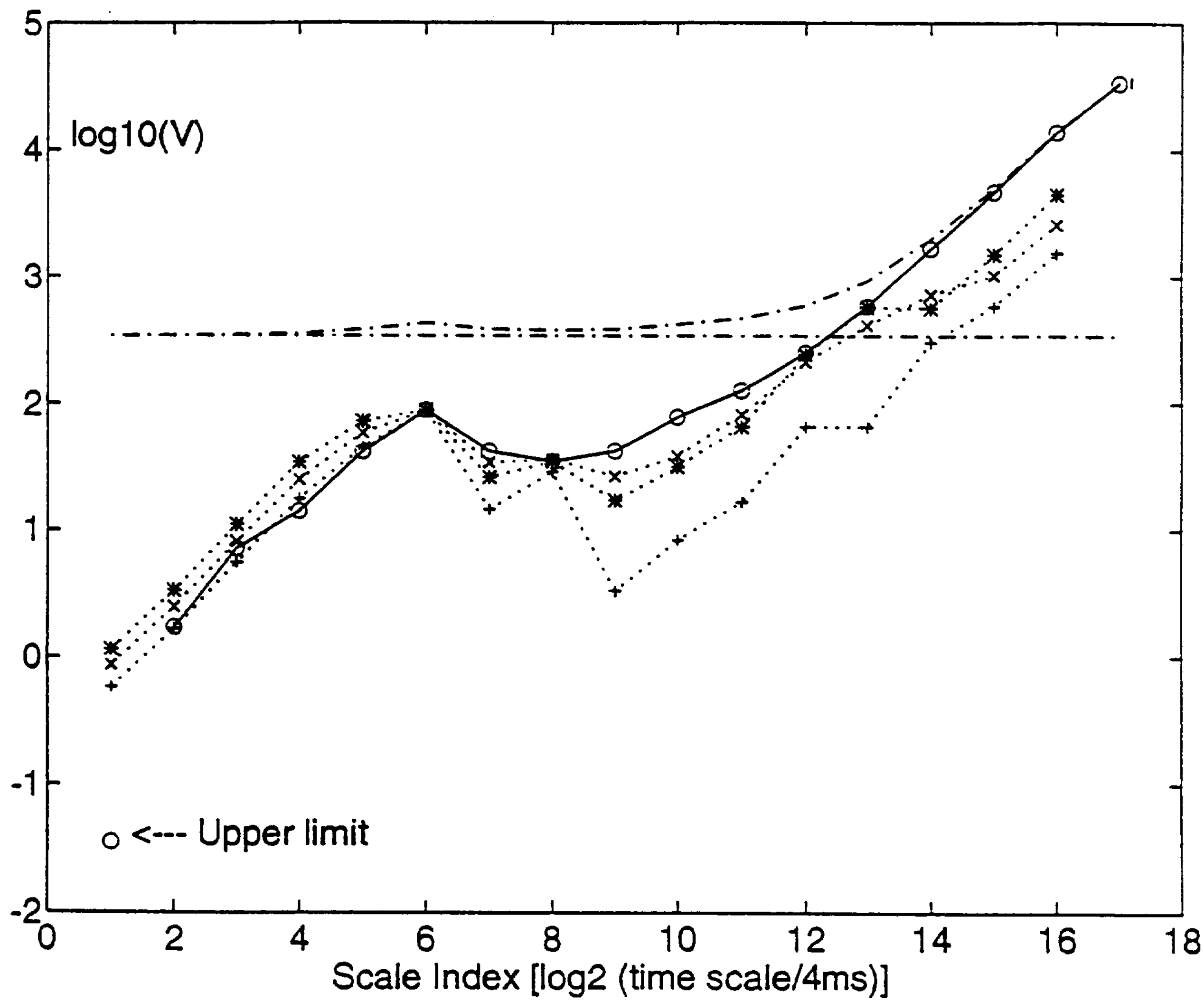
Time

6074



0 Site 127

Figure 44. Space-time diagram with site amplitudes plotted in the range [0,1] for the dripping handrail model with $s = .91$, $\omega = .1$ and 128 lattice sites. A uniformly distributed random initial condition with mean .3 and standard deviation .1 was used. 128 steps are shown, after approximately 6000 transient iterations.


log10(V)
<--- Upper limit
Scale Index [log2 (time scale/4ms)]
5
4
3
2
1
0
-1
-2
0
2
4
6
8
10
12
14
16
18

THE ASTROPHYSICAL JOURNAL SUPPLEMENT SERIES, 45:1–71, 1981 January

STUDIES IN ASTRONOMICAL TIME SERIES ANALYSIS. I. MODELING RANDOM PROCESSES IN THE TIME DOMAIN

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Received 1979 December 10; accepted 1980 May 14

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THE ASTROPHYSICAL JOURNAL, 343:874–887, 1989 August 15

STUDIES IN ASTRONOMICAL TIME SERIES ANALYSIS. III. FOURIER TRANSFORMS, AUTOCORRELATION FUNCTIONS, AND CROSS-CORRELATION FUNCTIONS OF UNEVENLY SPACED DATA

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ABSTRACT

This paper develops techniques to evaluate the discrete Fourier transform (DFT), the autocorrelation function (ACF), and the cross-correlation function (CCF) of time series which are not evenly sampled. The series may consist of quantized point data (e.g., yes/no processes such as photon arrival). The DFT, which can be inverted to recover the original data and the sampling, is used to compute correlation functions by means of a procedure which is effectively, but not explicitly, an interpolation. The CCF can be computed for two time series not even sampled at the same set of times. Techniques for removing the distortion of the correlation functions caused by the sampling, determining the value of a constant component to the data, and treating unequally weighted data are also discussed. FORTRAN code for the Fourier transform algorithm and numerical examples of the techniques are given.

Subject headings: analytical methods — BL Lacertae objects — numerical methods

I. THE PARADOX OF CORRELATION FUNCTIONS WITH UNEVENLY SAMPLED DATA

Correlation functions are useful time series analysis tools. They yield physical information such as the time scale of a process or the time delay between two related processes. But astronomical time series data are often unequally spaced in time, due to a variety of practical considerations. (The times may be irregular, or they be evenly spaced but with missing observations—"gaps.") Such unevenness produces a fundamental difficulty in the estimation of correlation functions, the resolution of which is the main point of this paper.

For data $X_n = X(t_n)$ sampled at evenly spaced times $t_n = (n-1)\Delta t$, $n = 1, 2, \ldots, N$ the traditional estimator of the autocorrelation function is

$$\rho_X(k) = (1/N) \sum_{n=1}^{N-k} X_n X_{n+k} . \quad \text{(I.1)}$$

This expression makes sense only if the sample times t_n are evenly spaced, since it can be thought of as a kind of vector dot product of X with X shifted in time by k. The times of the shifted data must match up with those of the unshifted data. Therefore the sampling interval must be constant and the lag k must be an integer multiple of this interval.

How should one estimate the ACF of unevenly sampled data? Possible approaches are to interpolate the data to even spacing and use equation (I.1), or to sum product-pairs $X(t_i)X(t_j)$ in bins of the lag $t_i - t_j$ (Mayo, Shay, and Riter 1974; Edelson and Krolik 1988). Gastner and Roberts (1975, 1977) circumvent the fact that the interval (t_n, t_{n+k}) is not a definite length of time, noting that statistically it does correspond to a fixed time interval—namely, k divided by the mean sampling rate. While these procedures may be satisfactory in some applications, they all produce some distortion and loss of information.

The goal of this work is a correlation function estimator which uses all of the information contained in unevenly spaced data. The proposed approach steps briefly into the frequency domain (computing the power spectrum) and returns to the time domain (computing the autocorrelation function with the Autocorrelation Theorem). While it does not explicitly interpolate, it can be thought of as effecting an implicit interpolation in the time domain. The basic tool of the computations is the discrete Fourier transform (§ II), which yields the power spectrum used in the computation of the autocorrelation function (§ III) and the cross-spectrum used to compute the cross-correlation function (§ IV). Examples using artificial data appear in all three of these sections. Section V exhibits correlation functions for some actual data on BL Lacertae—the prototype of a class of violently variable radio sources. The FORTRAN code for computing the discrete Fourier transform is given in Appendix A. Appendix B discusses the frequencies used in the inverse transformation. The remaining appendices treat an underlying constant component to the data, and unequally weighted data.

II. DISCRETE FOURIER TRANSFORM

This section presents an algorithm for the discrete Fourier transform (DFT) of unevenly sampled data. Later this transform will be used to estimate correlation functions, but it is of interest in its own right and in connection with power spectra.

Scargle (1982, hereafter Paper II) modified the classical definition of the DFT in order that the resulting power spectrum (or periodogram) of unevenly sampled data have the simple statistical behavior which obtains in the case of even sampling (Paper II, Appendix A), while maintaining time translation invariance (Paper II, Appendix B). In addition, spectral analysis using this estimator is equivalent to least-squares fitting of sine waves to the data (Paper II, Appendix C). Paper II dealt with power spectra, so the phase of the Fourier transform was unimportant; the present work differs slightly in correctly treating the complex phase of the transform.

Press and Teukolsky (1988) give an informative discussion of the beneficial properties of this periodogram, as well as a FORTRAN algorithm that uses a recurrence technique to gain a factor of 3 in speed. Further improvement is obtained with Press and Rybicki's (1989) clever $N \log N$ algorithm.

THE ASTROPHYSICAL JOURNAL, 359:469–482, 1990 August 20

STUDIES IN ASTRONOMICAL TIME SERIES ANALYSIS. IV. MODELING CHAOTIC AND RANDOM PROCESSES WITH LINEAR FILTERS

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Received 1989 February 13; accepted 1990 February 21

ABSTRACT

While chaos arises only in nonlinear systems, standard linear time series models are nevertheless useful for analyzing data from chaotic processes. This paper introduces such a model, the *chaotic moving average*. This time-domain model is based on the theorem that any chaotic process can be represented as the convolution of a linear filter with an uncorrelated process called the *chaotic innovation*. We also present a technique, *minimum phase-volume deconvolution*, to estimate the filter and innovation. The algorithm measures the quality of a model using the volume covered by the phase portrait of the innovation process. Experiments on synthetic data demonstrate the following properties of the algorithm: It accurately recovers the parameters of simple chaotic processes. Though tailored for chaos, the algorithm can detect both chaos and randomness, distinguish them from each other, and separate them if both are present. It can also recover non–minimum-delay pulse shapes in non-Gaussian processes, both random and chaotic.

Subject heading: numerical methods

I. CHAOTIC AND RANDOM PROCESSES

Nonlinear initial value problems often have solutions which are very sensitive to initial conditions, and which seem disordered—even though randomness does not appear explicitly in the equations. Very simple dynamical equations may have this property, called *chaos*. Scientists should be aware that data which seem random may actually be from a deterministic chaotic process.[1] Furthermore, chaos and randomness can be present in the same physical system. There is thus a need for techniques to identify and separate these two kinds of processes.

We take a chaotic process to be one that has the following properties: (1) disorder; (2) determinism; (3) sensitivity to initial conditions; (4) random initial conditions; (5) correlation function vanishes as the lag goes to infinity; (6) aperiodicity; (7) stationarity. More precisely, for a process to be chaotic almost all realizations must have these properties. For just as with random processes, some realizations—a set of measure zero—may fail to have any of these properties. These interdependent qualities are listed to give the flavor of chaos, not as a formal definition.

A brief discussion of these seven properties is in order. *Disorder*, or more properly *apparent disorder*, is most fundamental yet most difficult to define. A chaotic process is quite ordered, in that it obeys deterministic dynamics and is seen as such when properly viewed in its state space. But the process masquerades as disordered when viewed via the time series. As we will see, filtering is part of this masquerade. The primary goal of this paper is to provide tools to reveal this masquerade by simultaneously undoing the filtering and unveiling the hidden regularity.

Determinism means that if the initial conditions are precisely repeated, the system evolution over time is identical. But *sensitivity to initial conditions* means that as long as there is some difference between two initial values, no matter how small, eventually the two corresponding solutions radically diverge from each other. It is assumed that the *initial conditions are randomly chosen.*

Vanishing of the correlation function ensures that the solutions are truly disordered and diverge from each other never to return. The "taffy kneading" (stretch and fold) character of the dynamics usually supplies this feature (e.g., Berge, Pomeau, and Vidal 1984, Fig. VIII.8). In the important case that the correlation function is zero for all nonzero lags, the process is uncorrelated or "white" chaos, in analogy to white noise.

Aperiodicity is important because even for parameter values which place a system in its chaotic regime, the dynamical equations have periodic solutions for special initial values which comprise a set of measure zero. Such highly ordered solutions are not regarded as chaotic.

Stationarity means roughly that the statistical properties are independent of time. The explicit representation of the fact that the dynamical evolution leaves the probability distribution (often called the *invariant measure*) unchanged plays an important role in chaos theory. The initial conditions satisfy this same probability distribution.[2] Thus one cannot separate disorder due to the random initial conditions from that due to the convoluted way in which the past determines the future—they are manifestations of the same phenomenon, linked together by stationarity.

Chaotic time series can be generated by solving differential equations or by iterating return maps derived from the equations. Some problems (e.g., the evolution of generations of animals) are inherently discrete in time and the dynamics are completely represented by a recurrence equation. All examples in this paper are generated from recurrence equations and time is taken as discrete.

The goal of this series (Scargle 1981*a*, 1982, and 1988, hereafter respectively Papers I, II, and III) is to provide analysis

[1] A process is a procedure which generates time series. Each application of the procedure yields a time series, called a realization of the process.

[2] In principle the initial conditions can have any distribution. The process would then be not quite stationary, and one would have to worry about transients and nonrepresentative behavior (such as periodicity) for special initial values.

Studies in Astronomical Time Series Analysis V. Wavelets and the Scalegram

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National Aeronautics and Space Administration, Ames Research Center
Statistics Department, Stanford University

Abstract: This paper is intended to be a practical introduction to the use of wavelet methods in time series analysis. After introducing the reader to wavelets, with special emphasis on the Haar wavelet, we review the main uses of the methods for smoothing, compressing, and modeling time series data. We define the wavelet analog of the power spectrum, namely the scalegram. We compute the scalegram of a noisy signal, to show how it can be corrected for the presence of both additive obervational noise and the Poisson noise connected with the statistics of photons. We outline a smoothing procedure that is data-adaptive and should be useful for treating data that has jumps and other discontinuities. An appendix contains computer code (in FORTRAN and MatLab) for implementing all of the concepts of the paper: wavelet transforms, scalegrams, inverse wavelet transforms, and ideal smoothing techniques.

1. INTRODUCTION: WAVELETS FOR TIME SERIES ANALYSIS

The basic use of wavelets is the representation of an arbitrary function of time as a superposition of elementary functions – much as in Fourier analysis. The main difference is that the wavelets are localized in time; i.e. they do not extend over the entire interval, as do Fourier components (sines and cosines).

From a single wavelet shape (sometimes called the *analyzing wavelet*) one constructs an orthogonal basis of functions consisting of many copies of the basic shape scaled and translated in time. If $\psi(t)$ is the analyzing wavelet, then the scaled/translated wavelets are defined as follows:

$$\psi_{s,l}(t) = 2^{-s/2}\psi(2^{-s}t - l). \tag{1}$$

where the *scale index* s indicates the time-duration of the wavelets. Inspection of this equation shows that the wavelet width is proportional to

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THE QUASI-PERIODIC OSCILLATIONS AND VERY-LOW-FREQUENCY NOISE OF SCORPIUS X-1 AS TRANSIENT CHAOS: A DRIPPING HANDRAIL?

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Abstract: We present evidence that the quasi-periodic oscillations (QPO) and very low frequency noise (VLFN) characteristic of many accretion sources are different aspects of the same physical process. We analyzed a long, high time resolution EXOSAT observation of the low-mass x-ray binary (LMXB) Sco X-1. The x-ray luminosity varies stochastically on time scales from milliseconds to hours. The nature of this variability – as quantified with both power spectrum analysis and a new wavelet technique, the *scalegram* – agrees well with the *dripping handrail* accretion model, a simple dynamical system which exhibits *transient chaos.* In this model both the QPO and VLFN are produced by radiation from blobs with a wide size distribution, resulting from accretion and subsequent diffusion of hot gas, the density of which is limited by an unspecified instability to lie below a threshold.

subject headings: x-rays: stars – chaotic phenomena – accretion, accretion disks – methods: data analysis – stars: neutron

[1] National Research Council Postdoctoral Fellow

WAVELET SHRINKAGE AND W.V.D.: A 10-MINUTE TOUR

David L. Donoho
Stanford University

1. Introduction

With the rapid development of computerized scientific instruments comes a wide variety of interesting problems for data analysis and signal processing. In fields ranging from Extragalactic Astronomy to Molecular Spectroscopy to Medical Imaging to Computer Vision, one must recover a signal, curve, image, spectrum, or density from incomplete, indirect, and noisy data.

Recently, it has been shown by the author and his collaborators Iain Johnstone (Stanford), Gérard Kerkyacharian (Amiens), and Dominique Picard (Paris VII) that shrinking noisy wavelet coefficients via thresholding offers very attractive alternatives to existing methods of recovering signals from noisy data. Our new methods have theoretical properties of adaptive minimaxity that far surpass anything previously known. Other groups have independently developed methods for de-noising which are also based on wavelet thresholding in some sense. I think here of Mallat and collaborators (Courant), Coifman and collaborators (Yale), and Healy and collaborators (Dartmouth). These other groups have found that wavelet thresholding methods work well in problems ranging from photographic image restoration to medical imaging. R.A. DeVore (South Carolina) and B.J. Lucier (Purdue) have also come to thresholding, motivated by approximation-theoretic arguments. This agreement of diverse theoretical and empirical work is very encouraging, and suggests that wavelets will soon have a large impact on how scientists treat noisy data.

In this brief tour, I will only describe the mechanics of some wavelet shrinkage techniques and give examples. Software is available to compute all the displays presented in this paper; contact the author at `donoho@playfair.stanford.edu`. In the discussion I mention work which proves the various theoretical advantages of the new techniques.

Based on presentation at the International Conference on Wavelets and Applications, Toulouse, France, June, 1992. Supported by NSF DMS 92-09130. With appreciation to S. Roques and Y. Meyer for patience and encouragement. It is a pleasure to thank Iain Johnstone with whom many of these theoretical results have been derived, and Carl Taswell with whom Johnstone and I have developed the software used here.

Comparison of Temporal Analysis Methods in Search for Cosmological Time Dilation in Gamma-Ray Bursts

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Cosmic gamma-ray bursts (GRBs) are now the longest standing mystery in modern astronomy. They have been studied for a quarter century but a clear indication of their nature is not yet to be established. Bursters may be a very important astrophysical phenomenon in terms of energetics -- fluxes can be briefly two to three orders of magnitude higher than the all-sky background in the low- energy gamma-ray regime (~ 25 keV - few MeV). No simultaneous detection in another waveband has been obtained, nor have "interesting" counterparts been found during post-burst periods (within hours to days) in several arc minute- sized error regions. The most critical determinant for the GRB phenomenon, the source distance distribution, is almost completely unconstrained.

However, recent results (Meegan et al. 1992) from the Burst and Transient Source Experiment (BATSE) on the Compton Gamma Ray Observatory have begun to reveal a picture consistent with the bursters being at cosmological distances. BATSE may be sampling deep enough to see the effects of non-Euclidean space: The distribution of more than 500 burst localizations is isotropic to within sampling error, while the differential {Volume Observed / Volume Observable} relation indicates that BATSE sees "the edge" of the source distribution. This combination is most simply explained either by a nearby (< 1 pc) heliospheric burster distribution, or by a cosmological one (Z ~ unity). In fact, galactic disk populations are ruled out, and the extended halo hypothesis is constrained to ever larger sizes (core radius > 30 kpc) as more BATSE bursts are recorded.

If the cosmological explanation is correct, we must observe time dilation and redshift. Statistically, the time profiles of the most distant sources must be dilated -- with "stretch" factor of order {1+Z} ~ 2 -- relative to those of nearest sources, and their spectra (below quasi-power-law regime, <~ 100 keV) must appear "redder" by the same factor. For time dilation, the difficulty set us by Nature is that durations of bright bursts range over more than four orders of magnitude (!), clustering in the range ~ 5 - 20 s. Worse, burst profiles are notoriously complex and varied from burst to burst -- there is no standard temporal profile. In such circumstance, it is prudent to devise an analysis procedure that utilizes the temporal information maximally.

We describe four analysis methods for measuring the apparent time dilation effect (Norris et al. 1993). The most efficient test -- from an information theoretic standpoint -- completed so far is a wavelet decomposition of the GRB time profiles. This test indicates that, on average, dim bursts do have significantly more temporal structure than bright bursts on all time scales where signal dominates over noise (~ 2 s to 64 s). Simulations which calibrate the wavelet test indicate that the dimmest bursts would be at redshifts of order unity -- in agreement with inferences from the V/Vmax relation -- if in fact the cause is time dilation (Norris et al. 1993). We compare the results of this test with those of the other three, which also yield positive indications.

For all the tests, selection effects arising from intensity differences (factors up to ~ 300) are removed by rescaling all bursts' intensities and associated noise biases a uniform level. Because pulse widths in GRBs are energy-dependent (narrower at higher energy), spectral redshift is a competing effect which must be addressed in a (cosmologically) model-dependent manner. Means for ameliorating various potential pitfalls of these analyses are discussed.

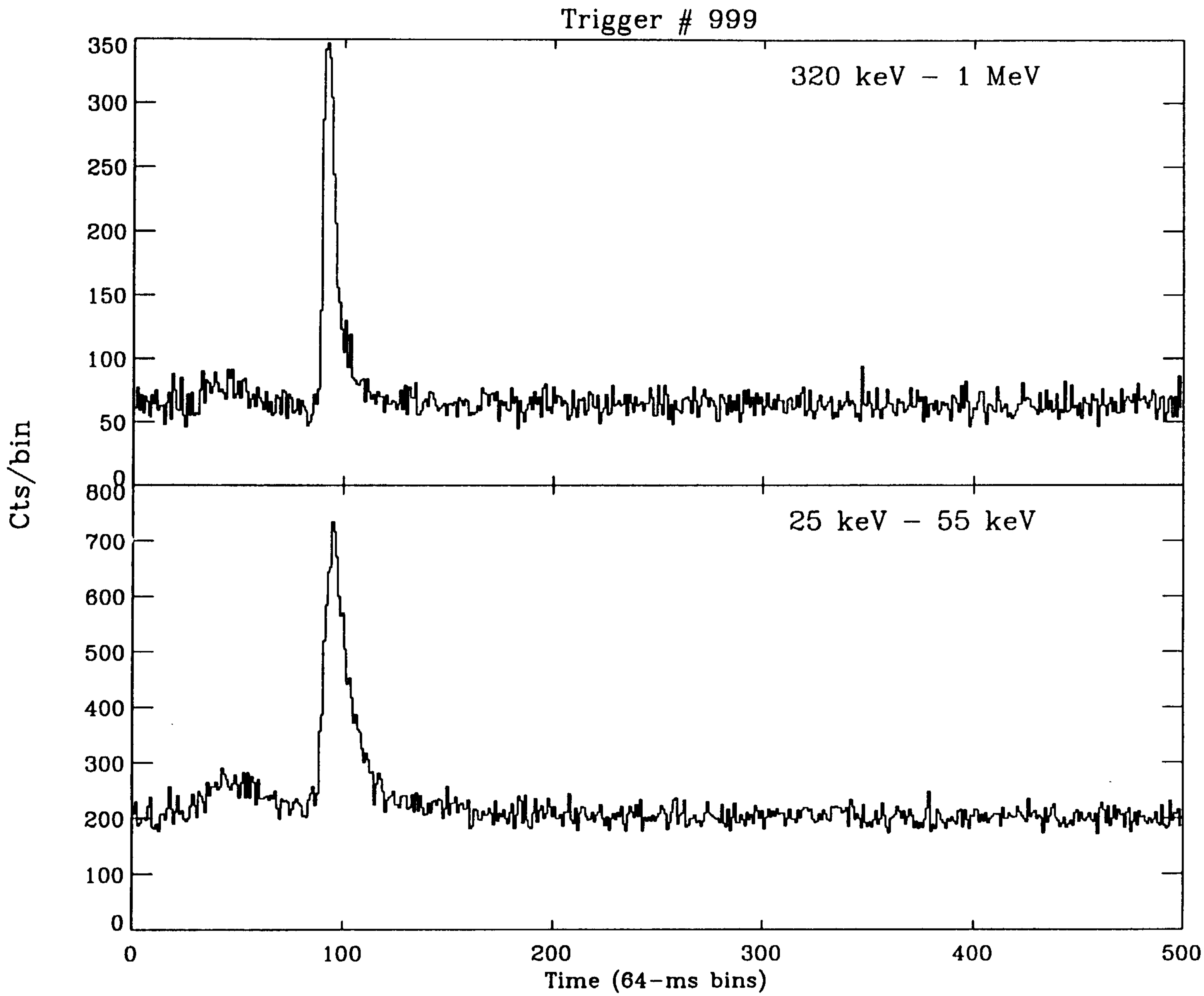
References

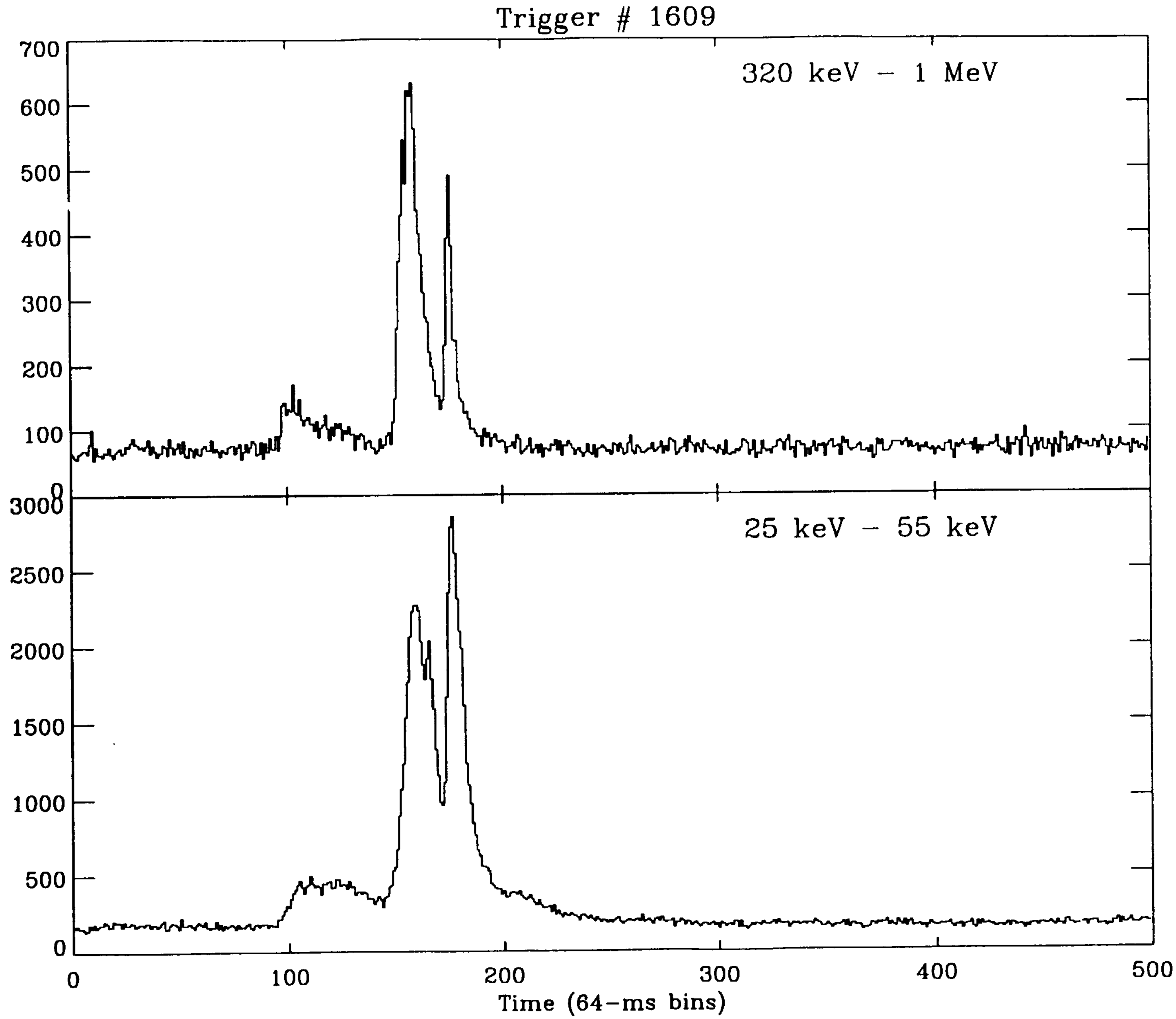
"Spatial distribution of gamma-ray bursts observed by BATSE," Meegan, C.A., et al. 1992, Nature, 355, p. 143.

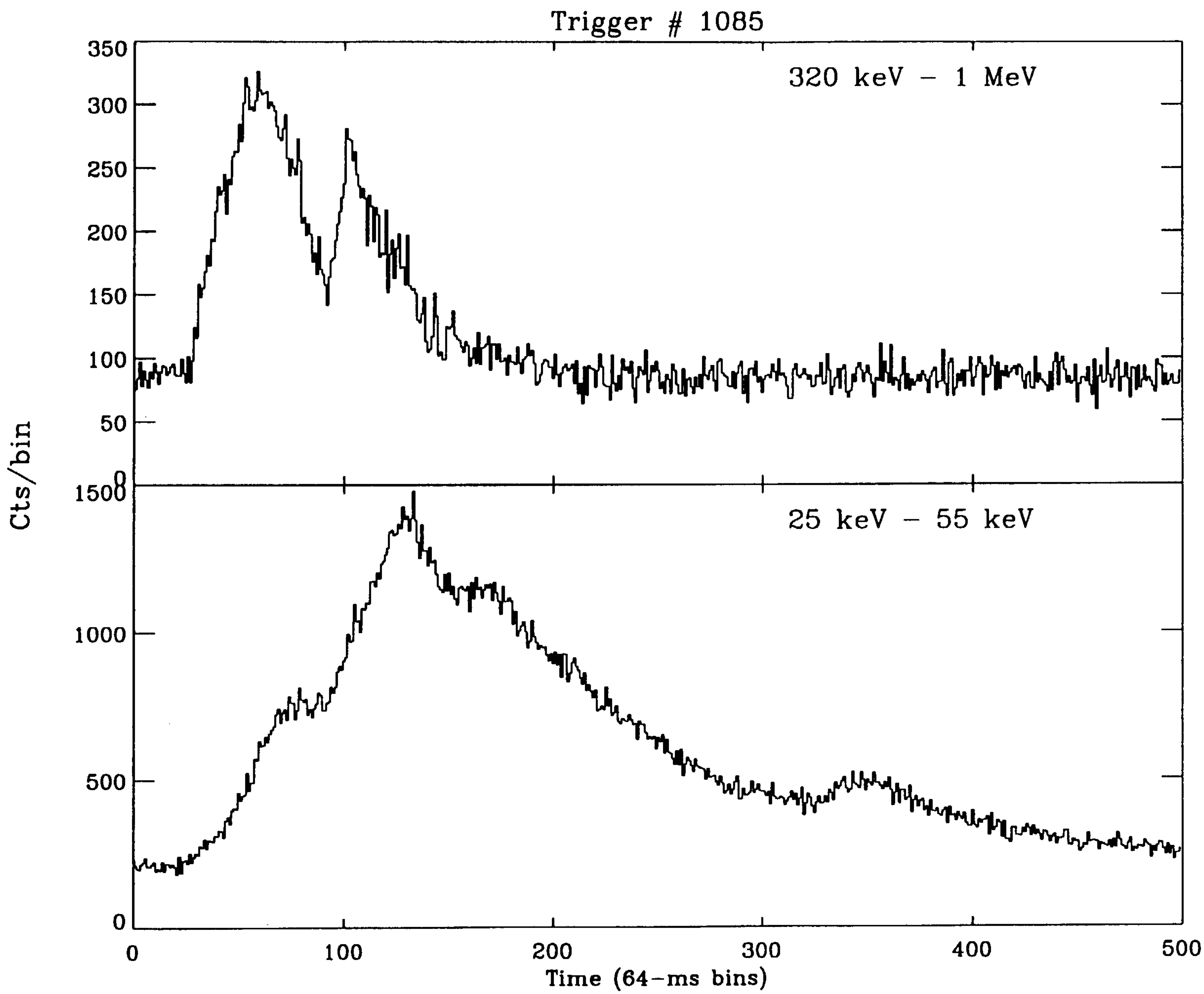
Possible Detection of Signature Consistent with Time Dilation in Gamma-Ray Bursts," Norris, J.P., et al., 1993, Proc. Compton Symp., St. Louis, in press.

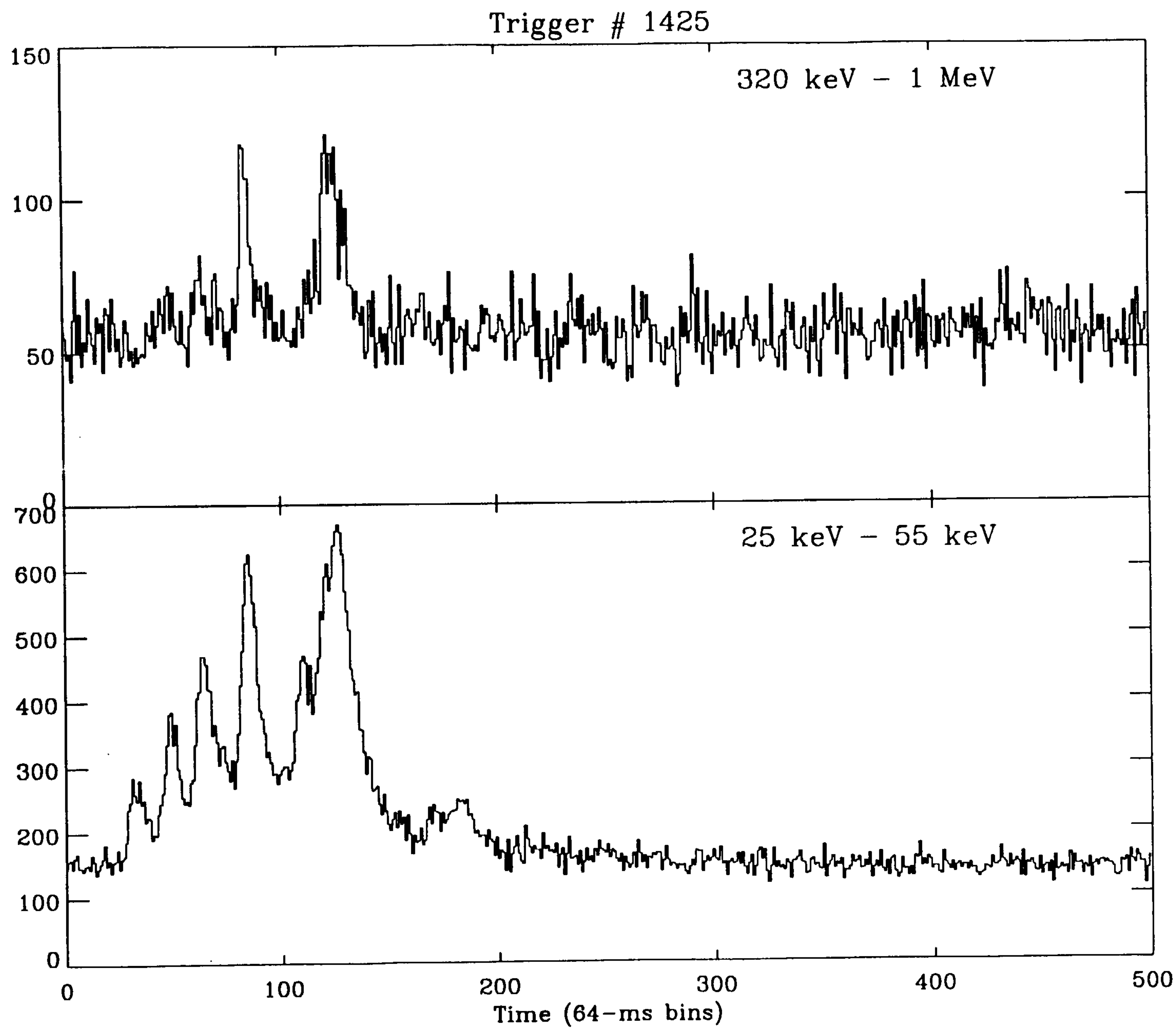
The following 10 figures give a flavor for the diverse temporal behavior observed in cosmic gamma-ray bursts, which may be the most energetic astrophysical phenomenon yet discovered. The plots are derived from high time resolution data available from BATSE (Burst and Transient Source Experiment, on the *Compton* Gamma Ray Observatory) when a burst "triggers" the instrument. Two-panel plots illustrate hard X-ray (bottom) and low-energy (top) γ-ray bands. Typical trend: pulses are narrower at higher energy. Total time interval plotted is 32 s, unless stated. The complexity frequently seen in long bursts can also be found in very brief ones – a manifestation of self-similarity? (cf. 7&8 with 9&10). Trigger #s identify events.

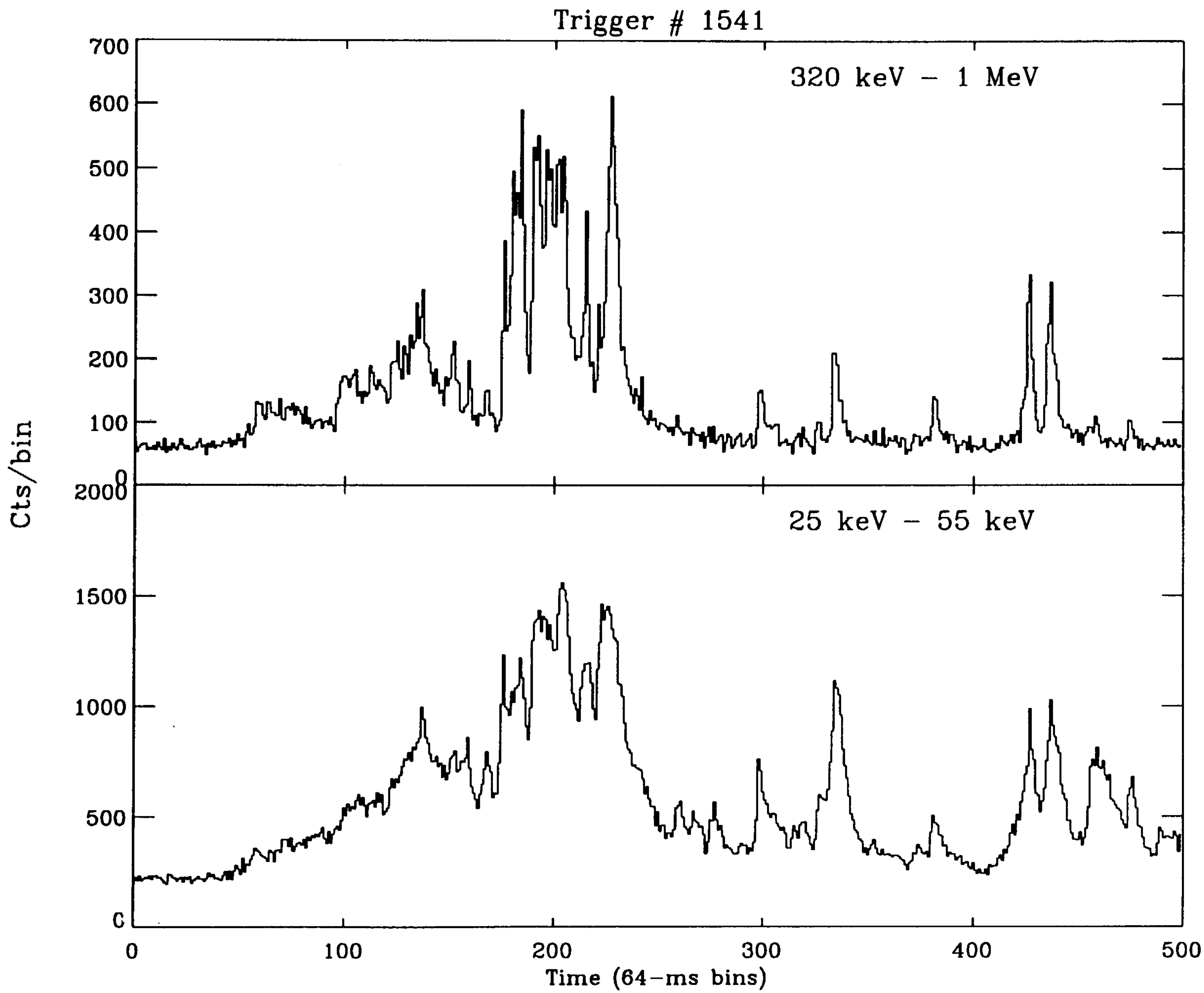
1. #999: example of a "FRED" (<u>F</u>ast <u>R</u>ise, quasi <u>E</u>xponential <u>D</u>ecay).
2. #1609: 2 or 3 overlapping FREDs, plus lower level emission (more FREDs?).
2. #1085: smooth event; much longer at lower energies and extra pulse near 350 s.
4. #1425: nearly periodic intervals (rare!) separating similarly shaped pulses.
5. #1541: complex, many-pulse event, lots of pulse overlap near 200 s.
6. #678: another complex example, with long low-energy tail (1000-s intv).
7. #2068: 250-ms blast and it's all over.
8. #2068: same event, 4-ms res., monolithic pulse with some spikes (0.5-s intv).
9. #2151: The "Super Bowl" burst (1/31/93). most intense BATSE burst – so far.
10. #2151: same event, 1st pulse, 2-ms res., short time-scale complexity (0.4-s intv).

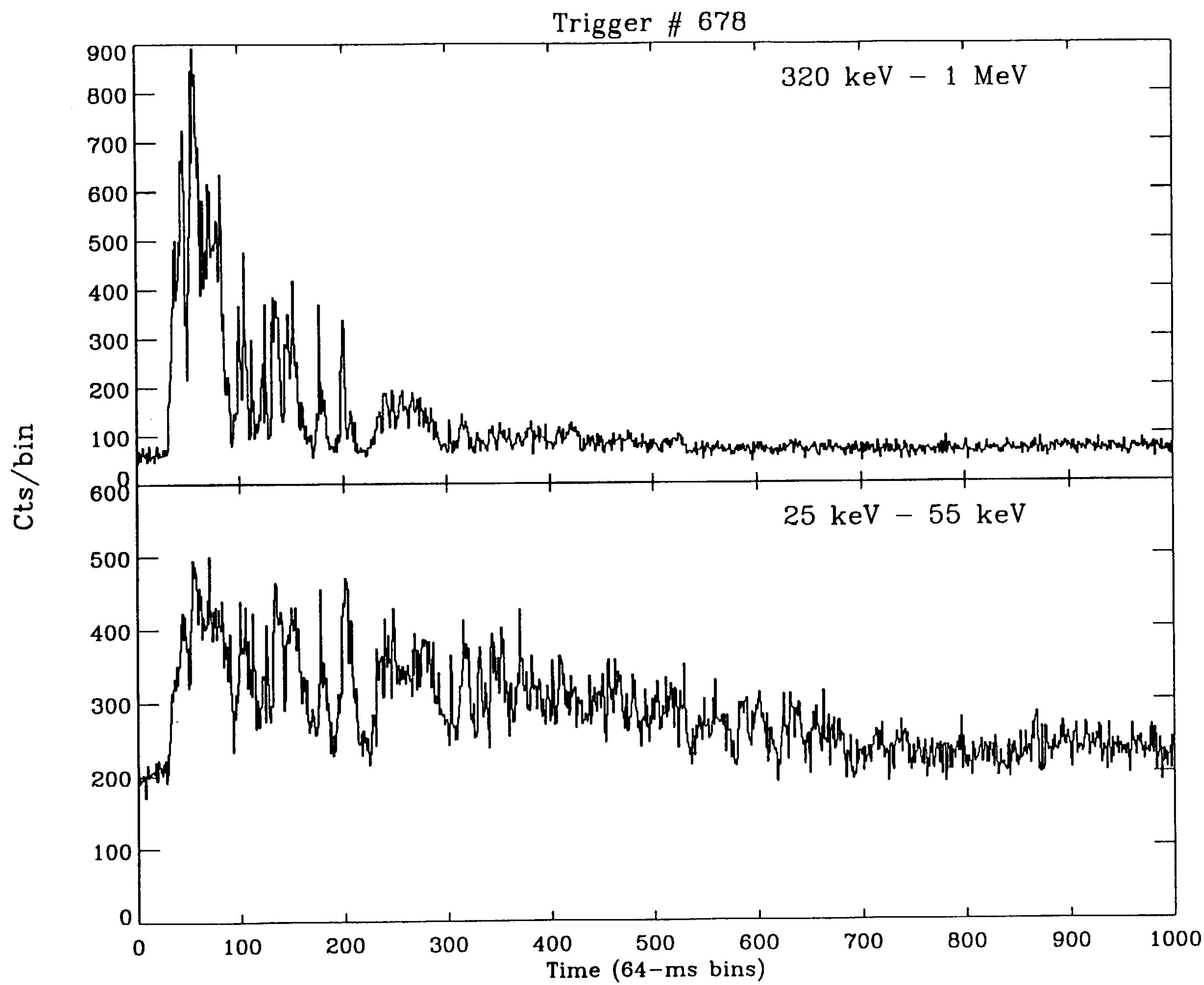

Trigger # 999
320 keV - 1 MeV
25 keV - 55 keV
Cts/bin
Time (64-ms bins)
0
100
200
300
400
500
350
300
250
200
150
100
50
0
800
700
600
500
400
300
200
100
0


Trigger # 1609
320 keV – 1 MeV
25 keV – 55 keV
Cts/bin
Time (64–ms bins)
0
100
200
300
400
500
600
700
1000
1500
2000
2500
3000


Trigger # 1085
320 keV - 1 MeV
25 keV - 55 keV
Cts/bin
Time (64-ms bins)
0
50
100
150
200
250
300
350
500
1000
1500
400

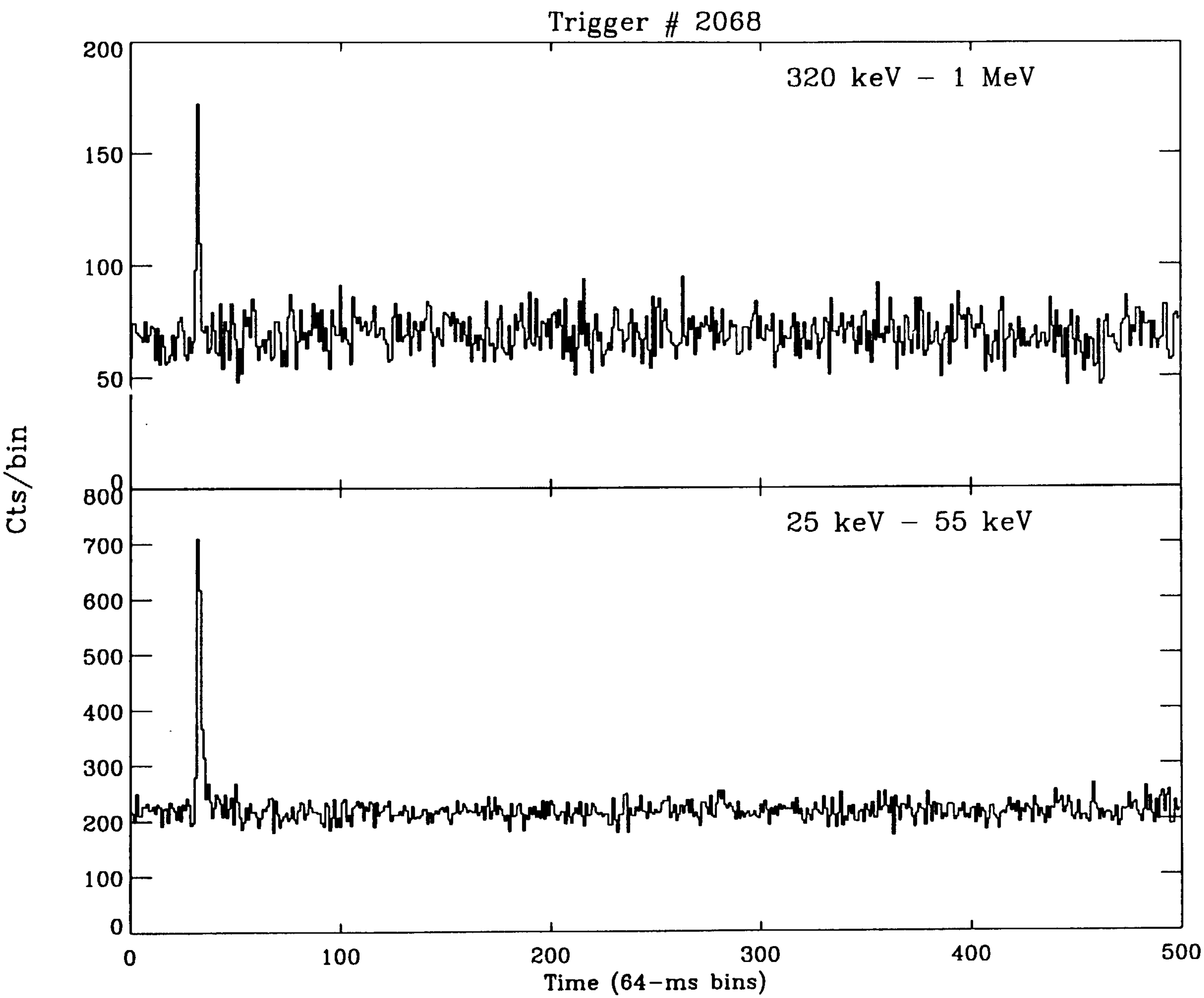

Trigger # 1425
320 keV - 1 MeV
25 keV - 55 keV
Cts/bin
Time (64-ms bins)
150
100
50
0
700
600
500
400
300
200
100
0
0
100
200
300
400
500


Trigger # 1541
320 keV – 1 MeV
25 keV – 55 keV
Cts/bin
Time (64–ms bins)
0
100
200
300
400
500
600
700
1000
1500
2000

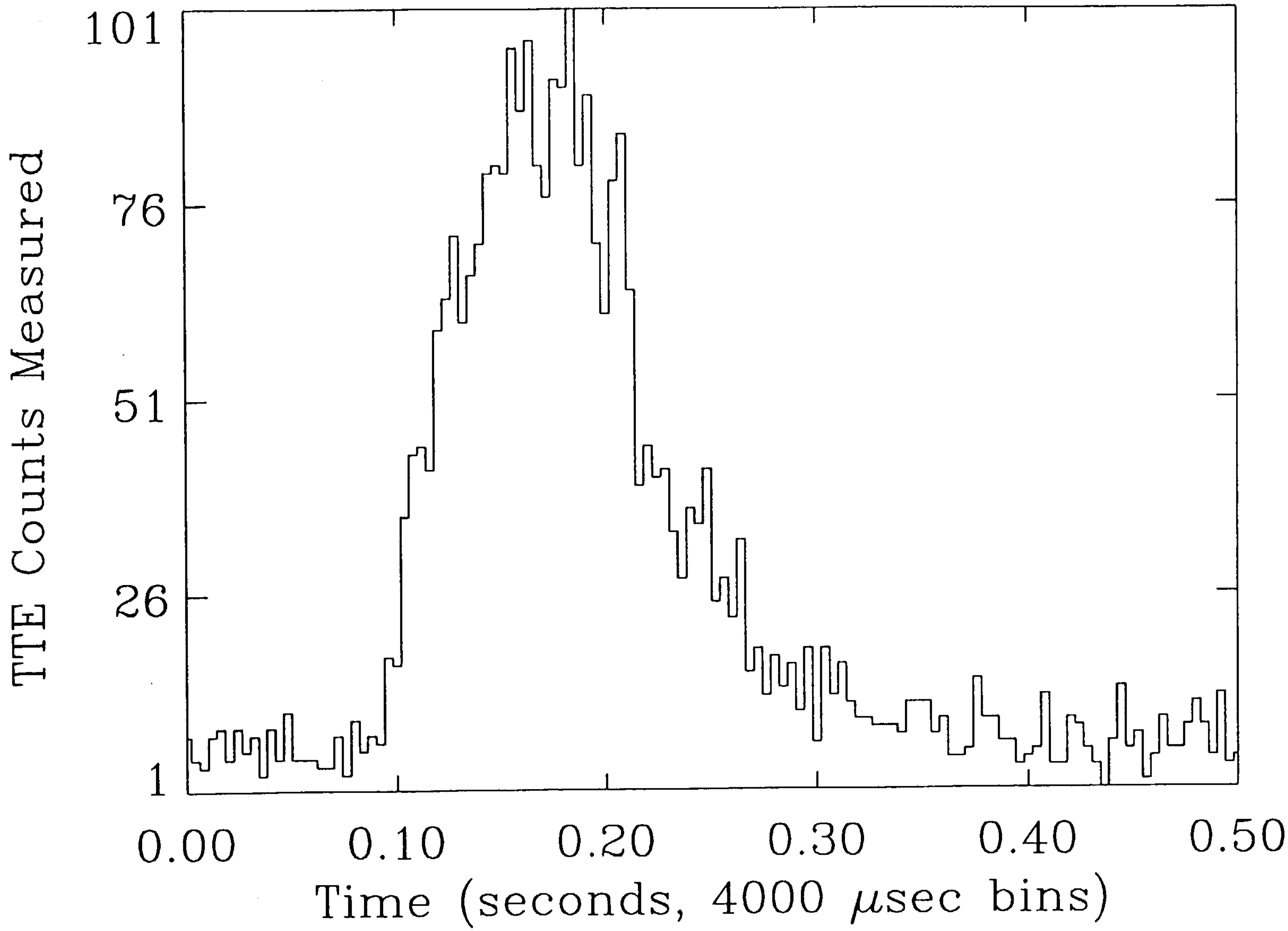


Trigger # 678
320 keV – 1 MeV
25 keV – 55 keV
Cts/bin
Time (64–ms bins)
0
100
200
300
400
500
600
700
800
900
1000

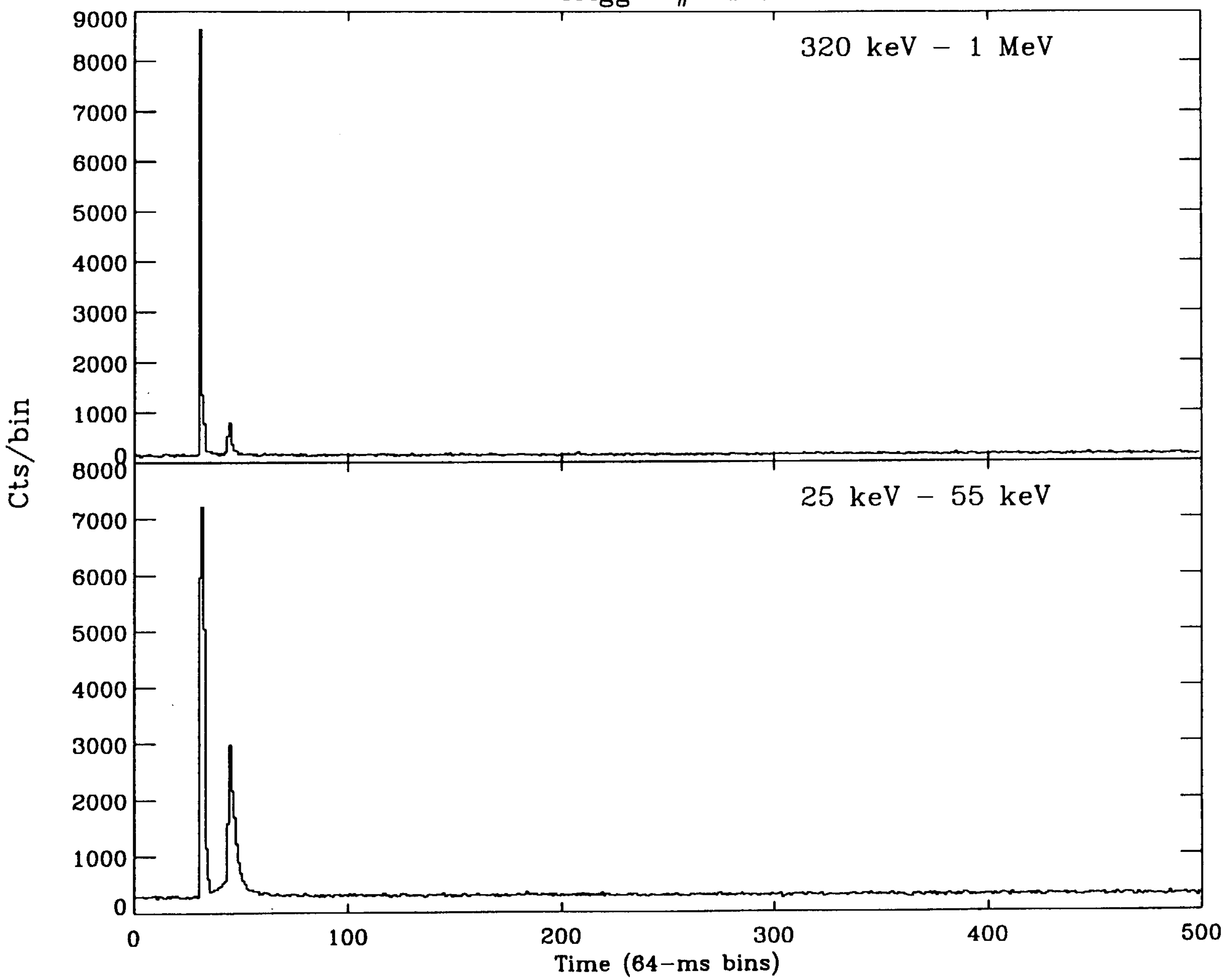
101

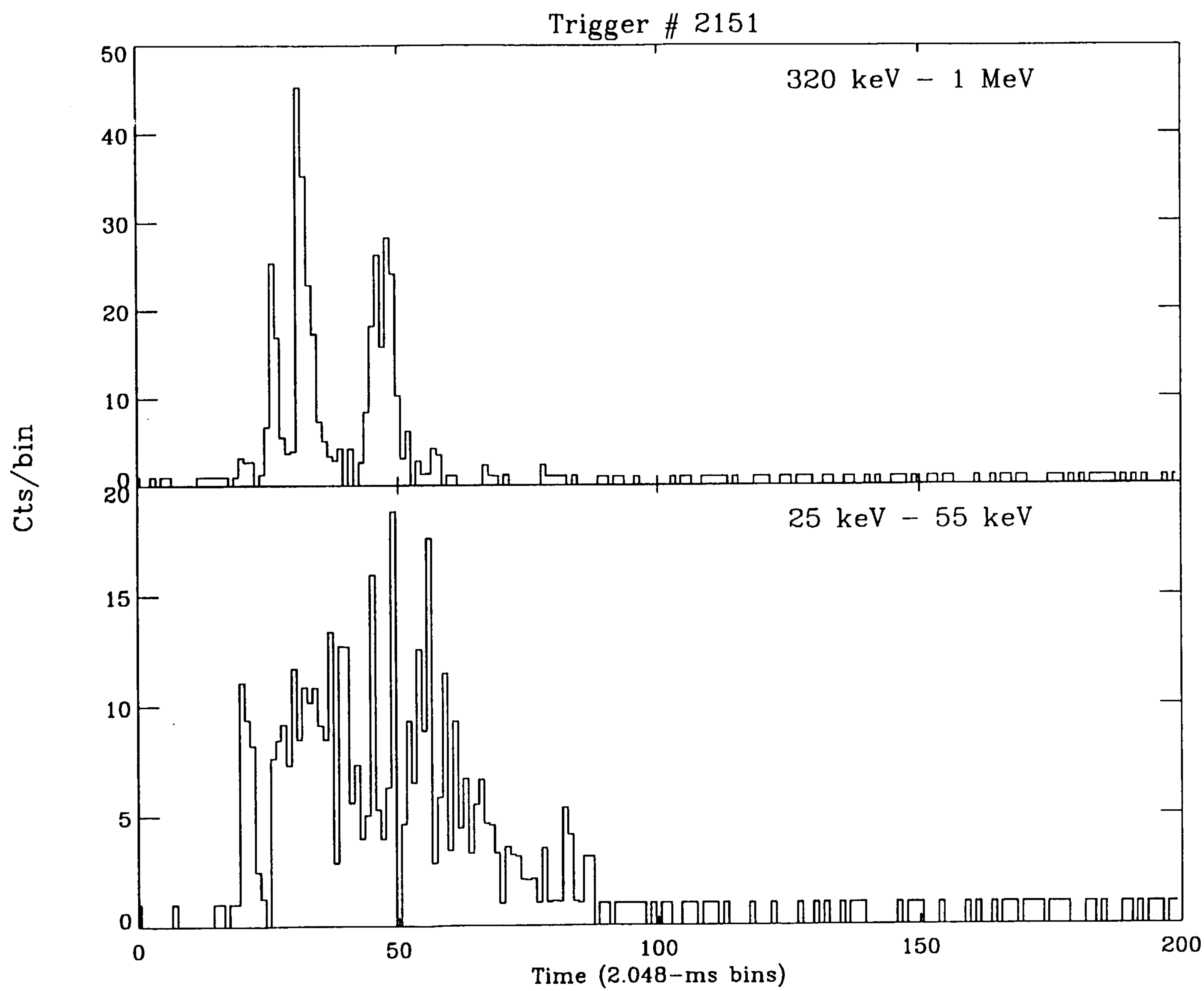

Trigger # 2068
320 keV – 1 MeV
25 keV – 55 keV
Cts/bin
Time (64–ms bins)
0
50
100
150
200
300
400
500
600
700
800

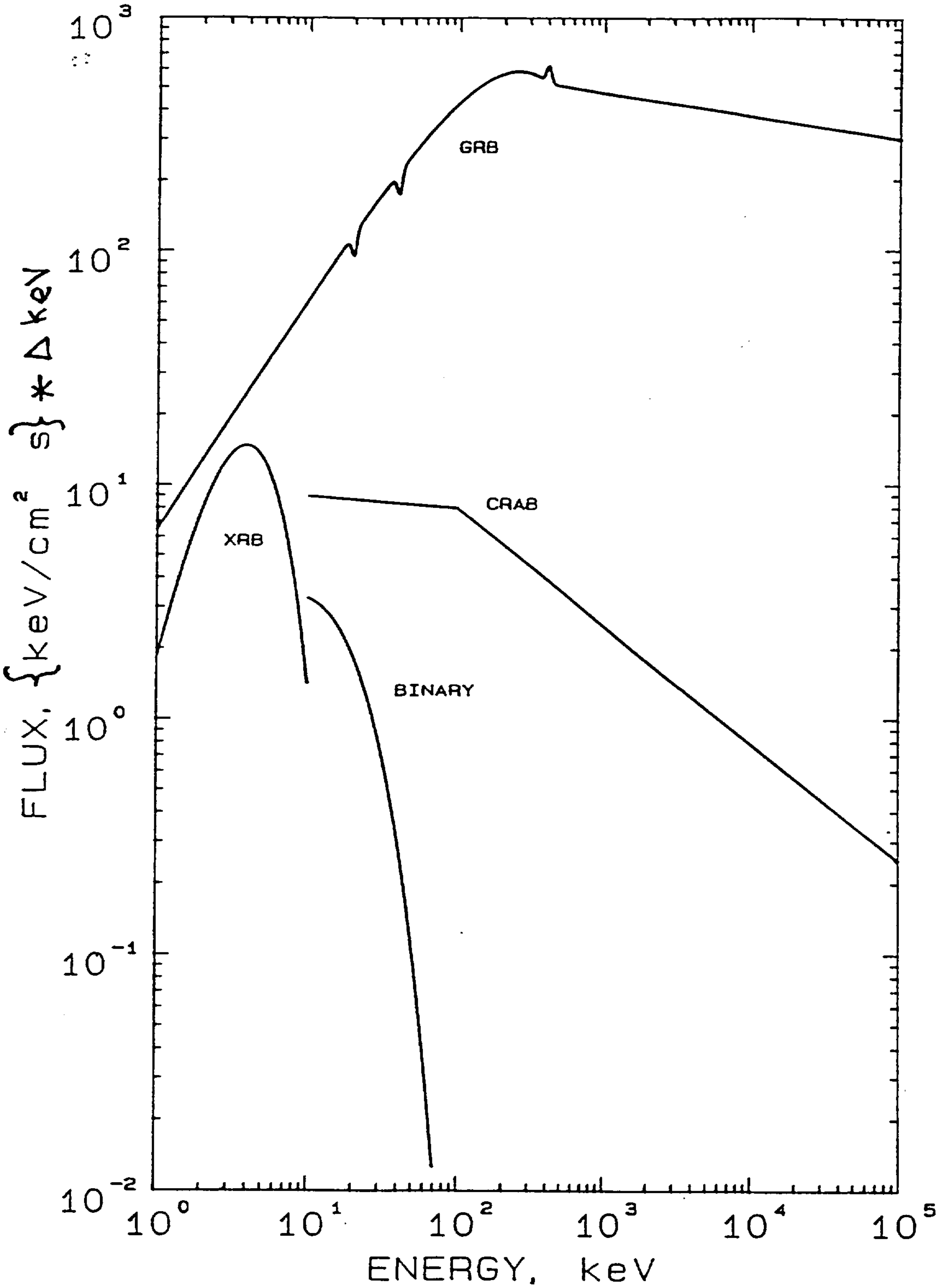
BATSE Trigger # 2068 LAD Dsc #3



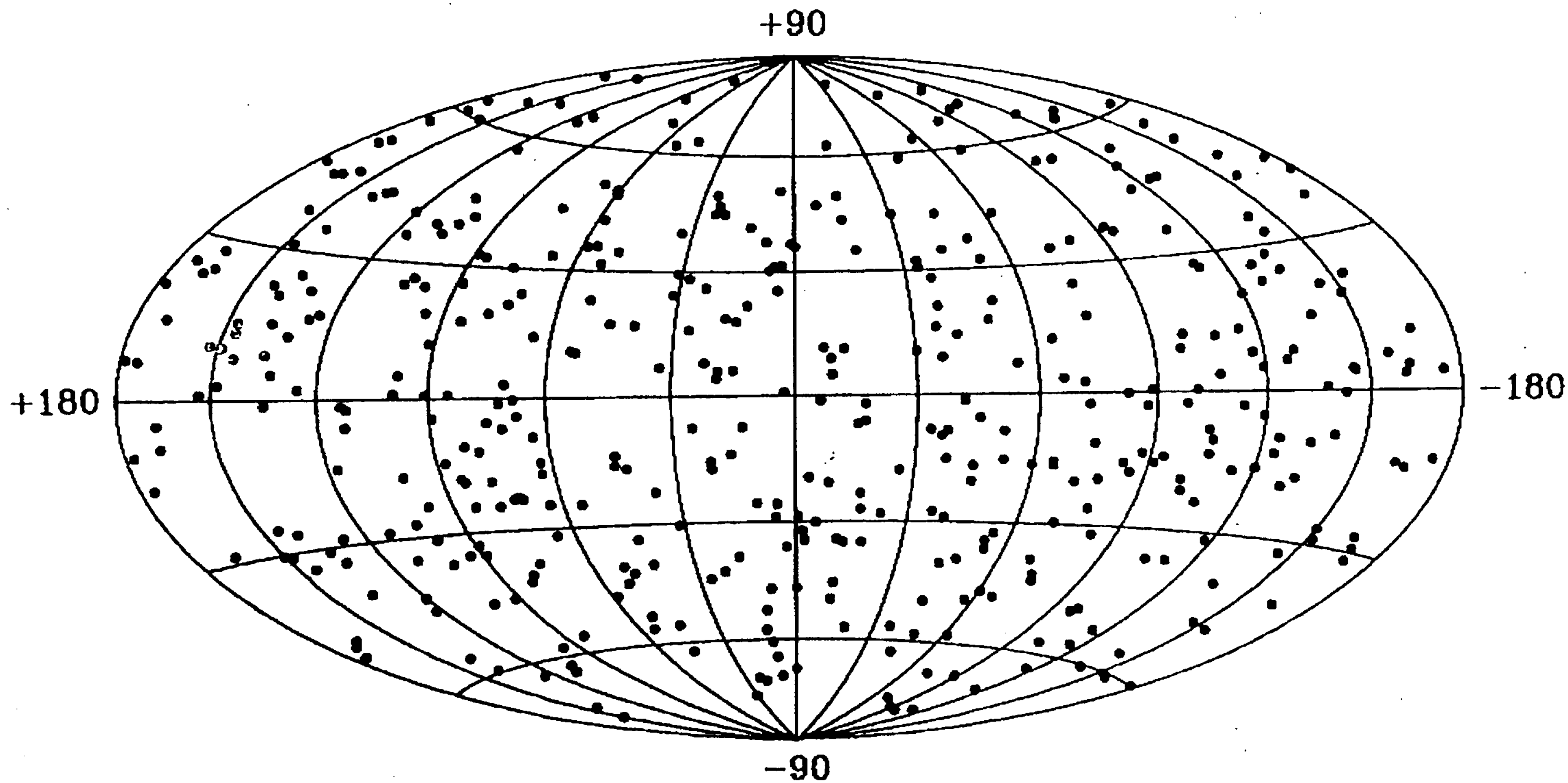
Trigger # 2151




Trigger # 2151
320 keV - 1 MeV
25 keV - 55 keV
Cts/bin
Time (2.048-ms bins)
0
50
100
150
200
10
20
30
40
5
15


GRB
CRAB
XRB
BINARY
FLUX, {keV/cm² s} * Δ keV
ENERGY, keV
10³
10²
10¹
10⁰
10⁻¹
10⁻²
10⁰
10¹
10²
10³
10⁴
10⁵

447 BATSE Gamma-Ray Bursts



Galactic Coordinates

107

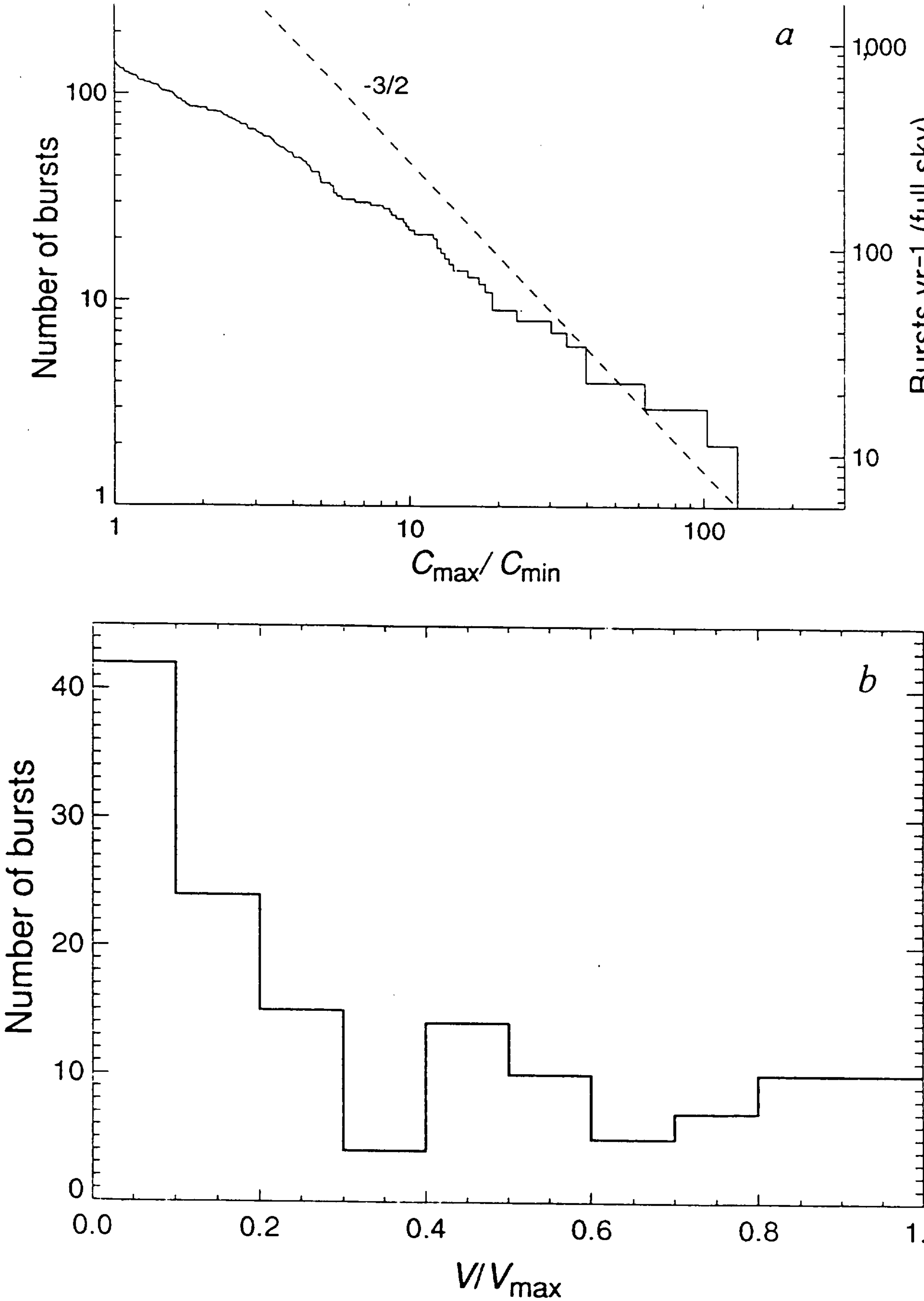


FIG. 1 *a*, Integral number distribution of 140 bursts as a function of peak rate. A −3/2 power law is expected for a homogeneous distribution of sources. The full sky rate is ~800 bursts per year. *b*, V/V_{max} distribution for 140 bursts. The average V/V_{max} is 0.348 ± 0.024. A uniform distribution is expected for a homogeneous distribution of sources.

The Great Astronomical Mystery Of the Last Third of the Twentieth Century: *How Distant Are the Gamma-Ray Bursters And What Are They ?*

The Known Facts:

GRBs are brightest high-energy celestial phenomenon, from X-rays (few keV) to nuclear γ-rays (few MeV) to GeV energies – hardest astrophysical spectra.

Temporal profiles are chaotic, unpredictable: durations ~ 10 msec to 1000 s.

No clear counterparts at *any* wavelength inside few-arcminute-square error boxes: Eliminates obvious candidates {X-ray stars, pulsars, galaxies, quasars}.

Isotropic celestial distribution – no concentration towards galactic plane or galactic center; no significant dipole or quadrupole moment.

Minimum distances from wavefront arrival time analysis with multiple-spacecraft observations: 10's of A.U. Maximum distances: unconstrained.

Depth of distribution: source density is inhomogeneous – there are not enough dim bursts, indicating we have sampled to the "edge" of the distribution.

Two natural solutions to the distance question: the source distribution could be either heliospheric ($d < 1$ pc) or cosmological ($d > 1$ Gpc).

Table 1

Model #	Author	Year Pub	Reference	Main Body	2nd Body	Place	Description
1.	Colgate	1968	CJPhys, 46, S476	ST		COS	SN shocks stellar surface in distant galaxy
2.	Colgate	1974	ApJ, 187, 333	ST		COS	Type II SN shock brem, inv Comp scat at stellar surface
3.	Stecker et al.	1973	Nature, 245, PS70	ST		DISK	Stellar superflare from nearby star
4.	Stecker et al.	1973	Nature, 245, PS70	WD		DISK	Superflare from nearby WD
5.	Harwit et al.	1973	ApJ, 186, L37	NS	COM	DISK	Relic comet perturbed to collide with old galactic NS
6.	Lamb et al.	1973	Nature, 246, PS52	WD	ST	DISK	Accretion onto WD from flare in companion
7.	Lamb et al.	1973	Nature, 246, PS52	NS	ST	DISK	Accretion onto NS from flare in companion
8.	Lamb et al.	1973	Nature, 246, PS52	BH	ST	DISK	Accretion onto BH from flare in companion
9.	Zwicky	1974	Ap&SS, 28, 111	NS		HALO	NS chunk contained by external pressure escapes, explodes
10.	Grindlay et al.	1974	ApJ, 187, L93	DG		SOL	Relativistic iron dust grain up-scatters solar radiation
11.	Brecher et al.	1974	ApJ, 187, L97	ST		DISK	Directed stellar flares on nearby stars
12.	Schlovskii	1974	SovAstron, 18, 390	WD	COM	DISK	Comet from system's cloud strikes WD
13.	Schlovskii	1974	SovAstron, 18, 390	NS	COM	DISK	Comet from system's cloud strikes NS
14.	Bisnovatyi- et al.	1975	Ap&SS, 35, 23	ST		COS	Absorption of neutrino emission from SN in stellar envelope
15.	Bisnovatyi- et al.	1975	Ap&SS, 35, 23	ST	SN	COS	Thermal emission when small star heated by SN shock wave
16.	Bisnovatyi- et al.	1975	Ap&SS, 35, 23	NS		COS	Ejected matter from NS explodes
17.	Pacini et al.	1974	Nature, 251, 399	NS		DISK	NS crustal starquake glitch; should time coincide with GRB
18.	Narlikar et al.	1974	Nature, 251, 590	WH		COS	White hole emits spectrum that softens with time
19.	Tsygan	1975	A&A, 44, 21	NS		HALO	NS corequake excites vibrations, changing E & B fields
20.	Chanmugam	1974	ApJ, 193, L75	WD		DISK	Convection inside WD with high B field produces flare
21.	Prilutski et al.	1975	Ap&SS, 34, 395	AGN	ST	COS	Collapse of supermassive body in nucleus of active galaxy
22.	Narlikar et al.	1975	Ap&SS, 35, 321	WH		COS	WH excites synchrotron emission, inverse Compton scattering
23.	Piran et al.	1975	Nature, 256, 112	BH		DISK	Inv Comp scat deep in ergosphere of fast rotating, accreting BH
24.	Fabian et al.	1976	Ap&SS, 42, 77	NS		DISK	NS crustquake shocks NS surface
25.	Chanmugan	1976	Ap&SS, 42, 83	WD		DISK	Magnetic WD suffers MHD instabilities, flares
26.	Mullan	1976	ApJ, 208, 199	WD		DISK	Thermal radiation from flare near magnetic WD
27.	Woosley et al.	1976	Nature, 263, 101	NS		DISK	Carbon detonation from accreted matter onto NS
28.	Lamb et al.	1977	ApJ, 217, 197	NS		DISK	Mag gating of accret disk around NS causes sudden accretion
29.	Piran et al.	1977	ApJ, 214, 268	BH		DISK	Instability in accretion onto rapidly rotating BH
30.	Dasgupta	1979	Ap&SS, 63, 517	DG		SOL	Charged intergal rel dust grain enters sol sys, breaks up
31.	Tsygan	1980	A&A, 87, 224	WD		DISK	WD surface nuclear burst causes chromospheric flares
32.	Tsygan	1980	A&A, 87, 224	NS		DISK	NS surface nuclear burst causes chromospheric flares
33.	Ramaty et al.	1981	Ap&SS, 75, 193	NS		DISK	NS vibrations heat atm to pair produce, annihilate, synch cool
34.	Newman et al.	1980	ApJ, 242, 319	NS	AST	DISK	Asteroid from interstellar medium hits NS
35.	Ramaty et al.	1980	Nature, 287, 122	NS		HALO	NS core quake caused by phase transition, vibrations
36.	Howard et al.	1981	ApJ, 249, 302	NS	AST	DISK	Asteroid hits NS, B-field confines mass, creates high temp
37.	Mitrofanov et al.	1981	Ap&SS, 77, 469	NS		DISK	Helium flash cooled by MHD waves in NS outer layers
38.	Colgate et al.	1981	ApJ, 248, 771	NS	AST	DISK	Asteroid hits NS, tidally disrupts, heated, expelled along B lines
39.	van Buren	1981	ApJ, 249, 297	NS	AST	DISK	Asteroid enters NS B field, dragged to surface collision
40.	Kuznetsov	1982	CosRes, 20, 72	MG		SOL	Magnetic reconnection at heliopause
41.	Katz	1982	ApJ, 260, 371	NS		DISK	NS flares from pair plasma confined in NS magnetosphere
42.	Woosley et al.	1982	ApJ, 258, 716	NS		DISK	Magnetic reconnection after NS surface He flash
43.	Fryxell et al.	1982	ApJ, 258, 733	NS		DISK	He fusion runaway on NS B-pole helium lake
44.	Hameury et al.	1982	A&A, 111, 242	NS		DISK	e- capture triggers H flash triggers He flash on NS surface
45.	Mitrofanov et al.	1982	MNRAS, 200, 1033	NS		DISK	B induced cyclo res in rad absorp giving rel e-s, inv C scat
46.	Fenimore et al.	1982	Nature, 297, 665	NS		DISK	BB X-rays inv Comp scat by hotter overlying plasma
47.	Lipunov et al.	1982	Ap&SS, 85, 459	NS	ISM	DISK	ISM matter accum at NS magnetopause then suddenly accretes
48.	Baan	1982	ApJ, 261, L71	WD		HALO	Nonexplosive collapse of WD into rotating, cooling NS
49.	Ventura et al.	1983	Nature, 301, 491	NS	ST	DISK	NS accretion from low mass binary companion
50.	Bisnovatyi- et al.	1983	Ap&SS, 89, 447	NS		DISK	Neutron rich elements to NS surface with quake, undergo fission
51.	Bisnovatyi- et al.	1984	SovAstron, 28, 62	NS		DISK	Thermonuclear explosion beneath NS surface
52.	Ellison et al.	1983	A&A, 128, 102	NS		HALO	NS corequake + uneven heating yield SGR pulsations
53.	Hameury et al.	1983	A&A, 128, 369	NS		DISK	B field contains matter on NS cap allowing fusion
54.	Bonazzola et al.	1984	A&A, 136, 89	NS		DISK	NS surface nuc explosion causes small scale B reconnection
55.	Michel	1985	ApJ, 290, 721	NS		DISK	Remnant disk ionization instability causes sudden accretion
56.	Liang	1984	ApJ, 283, L21	NS		DISK	Resonant EM absorp during magnetic flare gives hot synch e-s
57.	Liang et al.	1984	Nature, 310, 121	NS		DISK	NS magnetic fields get twisted, recombine, create flare
58.	Mitrofanov	1984	Ap&SS, 105, 245	NS		DISK	NS magnetosphere excited by starquake
59.	Epstein	1985	ApJ, 291, 822	NS		DISK	Accretion instability between NS and disk
60.	Schlovskii et al.	1985	MNRAS, 212, 545	NS		HALO	Old NS in Galactic halo undergoes starquake
61.	Tsygan	1984	Ap&SS, 106, 199	NS		DISK	Weak B field NS spherically accretes, Comptonizes X-rays
62.	Usov	1984	Ap&SS, 107, 191	NS		DISK	NS flares result of magnetic convective-oscillation instability
63.	Hameury et al.	1985	ApJ, 293, 56	NS		DISK	High Landau e-s beamed along B lines in cold atm. of NS
64.	Rappaport et al.	1985	Nature, 314, 242	NS		DISK	NS + low mass stellar companion gives GRB + optical flash
65.	Tremaine et al.	1986	ApJ, 301, 155	NS	COM	DISK	NS tides disrupt comet, debris hits NS next pass
66.	Muslimov et al.	1986	Ap&SS, 120, 27	NS		HALO	Radially oscillating NS
67.	Sturrock	1986	Nature, 321, 47	NS		DISK	Flare in the magnetosphere of NS accelerates e-s along B-field
68.	Paczynski	1986	ApJ, 308, L43	NS		COS	Cosmo GRBs: rel e+/- opt thk plasma outflow indicated
69.	Bisnovatyi- et al.	1986	SovAstron, 30, 582	NS		DISK	Chain fission of superheavy nuclei below NS surface during SN
70.	Alcock et al.	1986	PRL, 57, 2088	SS	SS	DISK	SN ejects strange mat lump craters rotating SS companion
71.	Vahai et al.	1988	A&A, 207, 55	ST		DISK	Magnetically active stellar system gives stellar flare
72.	Babul et al.	1987	ApJ, 316, L49	CS		COS	GRB result of energy released from cusp of cosmic string
73.	Livio et al.	1987	Nature, 327, 398	NS	COM	DISK	Oort cloud around NS can explain soft gamma-repeaters
74.	McBreen et al.	1988	Nature, 332, 234	GAL	AGN	COS	G-wave bkgrd makes BL Lac wiggle across galaxy lens caustic
75.	Curtis	1988	ApJ, 327, L81	WD		COS	WD collapses, burns to form new class of stable particles
76.	Melia	1988	ApJ, 335, 965	NS		DISK	Be/X-ray binary sys evolves to NS accretion with recurrence
77.	Ruderman et al.	1988	ApJ, 335, 306	NS		DISK	e+/- cascades by aligned pulsar outer-mag-sphere reignition
78.	Paczynski	1988	ApJ, 335, 525	CS		COS	Energy released from cusp of cosmic string (revised)
79.	Murikami et al.	1988	Nature, 335, 234	NS		DISK	Absorption features suggest separate colder region near NS
80.	Melia	1988	Nature, 336, 658	NS		DISK	NS + accretion disk reflection explains GRB spectra
81.	Blaes et al.	1989	ApJ, 343, 839	NS		DISK	NS seismic waves couple to magnetospheric Alfen waves
82.	Trofimenko et al.	1989	Ap&SS, 152, 105	WH		COS	Kerr-Newman white holes
83.	Sturrock et al.	1989	ApJ, 346, 950	NS		DISK	NS E- field accelerates electrons which then pair cascade

84.	Fenimore et al.	1988	ApJ, 335, L71	NS		DISK	Narrow absorption features indicate small cold area on NS
85.	Rodrigues	1989	AJ, 98, 2280	WD	WD	DISK	Binary member loses part of crust, through L1, hits primary
86.	Pineault et al.	1989	ApJ, 347, 1141	NS	COM	DISK	Fast NS though Oort clouds, fast WD bursts only optical
87.	Melia et al.	1989	ApJ, 346, 378	NS		DISK	Episodic electrostatic accel and Comp scat from rot high-B NSs
88.	Trofimenko	1989	Ap&SS, 159, 301	WH		COS	Different types of white, "grey" holes can emit GRB
89.	Eichler et al.	1989	Nature, 340, 126	NS	NS	COS	NS - NS binary members collide, coalesce
90.	Wang et al.	1989	PRL, 63, 1550	NS		DISK	Cyclo res & Raman scat fits 20, 40 keV dips, magnetized NS
91.	Alexander et al.	1989	ApJ, 344, L1	NS		DISK	QED mag resonant opacity in NS atmosphere
92.	Melia	1990	ApJ, 351, 601	NS		DISK	NS magnetospheric plasma oscillations
93.	Ho et al.	1990	ApJ, 348, L25	NS		DISK	Beaming of radiation necessary from magnetized neutron stars
94.	Mitrofanov et al.	1990	Ap&SS, 165, 137	NS	COM	DISK	Interstellar comets pass through dead pulsar's magnetosphere
95.	Dermer	1990	ApJ, 360, 197	NS		DISK	Compton scattering in strong NS magnetic field
96.	Blaes et al.	1990	ApJ, 363, 612	NS	ISM	DISK	Old NS accretes from ISM, surface goes nuclear
97.	Paczynski	1990	ApJ, 363, 218	NS	NS	COS	NS-NS collision causes v collisions to drive super-Ed wind
98.	Zdziarski et al.	1991	ApJ, 366, 343	RE	MBR	COS	Scattering of microwave background photons by rel e-s
99.	Pineault	1990	Nature, 345, 233	NS	COM	DISK	Young NS drifts through its own Oort cloud
100.	Trofimenko et al.	1991	Ap&SS, 178, 217	WH		HALO	White hole supernova gave simul burst of g-waves from 1987A
101.	Melia et al.	1991	ApJ, 373, 198	NS		DISK	NS B- field undergoes resistive tearing, accelerates plasma
102.	Holcomb et al.	1991	ApJ, 378, 682	NS		DISK	Alfen waves in non-uniform NS atmosphere accelerate particles
103.	Haensel et al.	1991	ApJ, 375, 209	SS	SS	COS	Strange stars emit binding energy in grav. rad. and collide
104.	Blaes et al.	1991	ApJ, 381, 210	NS	ISM	DISK	Slow interstellar accretion onto NS, e- capture starquakes result
105.	Frank et al.	1992	ApJ, 385, L45	NS		DISK	Low mass X-ray binary evolves into GRB sites
106.	Woosley et al.	1992	ApJ, 391, 228	NS		HALO	Accreting WD collapses to NS
107.	Dar et al.	1992	ApJ, 388, 164	WD		COS	WD accretes to form naked NS, GRBs, cosmic rays
108.	Hanami	1992	ApJ, 389, L71	NS	PLAN	COS	NS - planet magnetospheric interaction unstable
109.	Meszaros et al.	1992	ApJ, 397, 570	NS	NS	COS	NS - NS collision produces anisotropic fireball
110.	Carter	1992	ApJ, 391, L67	BH	ST	COS	Normal stars tidally disrupted by galactic nucleus BH
111.	Usov	1992	Nature, 357, 472	NS		COS	WD collapses to form NS, B-field brakes NS rotation instantly
112.	Narayan et al.	1992	ApJ, 395, L83	NS	NS	COS	NS - NS merger gives optically thick fireball
113.	Narayan et al.	1992,	ApJ, 395, L83	BH	NS	COS	BH-NS merger gives optically thick fireball
114.	Brainerd	1992	ApJ, 394, L33	AGN	JET	COS	Synchrotron emission from AGN jets
115.	Meszaros et al.	1992	MNRAS, 257, 29P	BH	NS	COS	BH-NS have vs collide to γs in clean fireball
116.	Meszaros et al.	1992	MNRAS, 257, 29P	NS	NS	COS	NS-NS have vs collide to γs in clean fireball
117.	Cline et al.	1992	ApJ, 401, L57	BH		DISK	Primordial BHs evaporating could account for short hard GRBs
118.	Rees et al.	1992	MNRAS, 258, 41P	NS	ISM	COS	Relativistic fireball reconverted to radiation when hits ISM

A mostly complete list of refereed papers on possible physical models for the gamma-ray burst phenomenon. Does not include papers treating only radiation transfer, nor unrefereed conference papers.

Seventh column indicates scale of GRB origin:
COS = cosmological (metagalactic, ~ Gigaparsecs); DISK = galactic disk (~ 100 parsecs); HALO = galactic halo (~ tens of kiloparsecs); SOL = solar environs (< 1 parsec). Note preference for cosmological scenarios, previously eschewed, after appearance of BATSE results on isotropy, source density inhomogeneity (late 1991)!

More than 100 combinatorial possibilities have been explored!

From: "A 'Century' of Gamma-Ray Burst Models", R.J. Nemiroff, Comments on Astrophysics, 1993, in press.

Tests for Time Dilation in GRBs

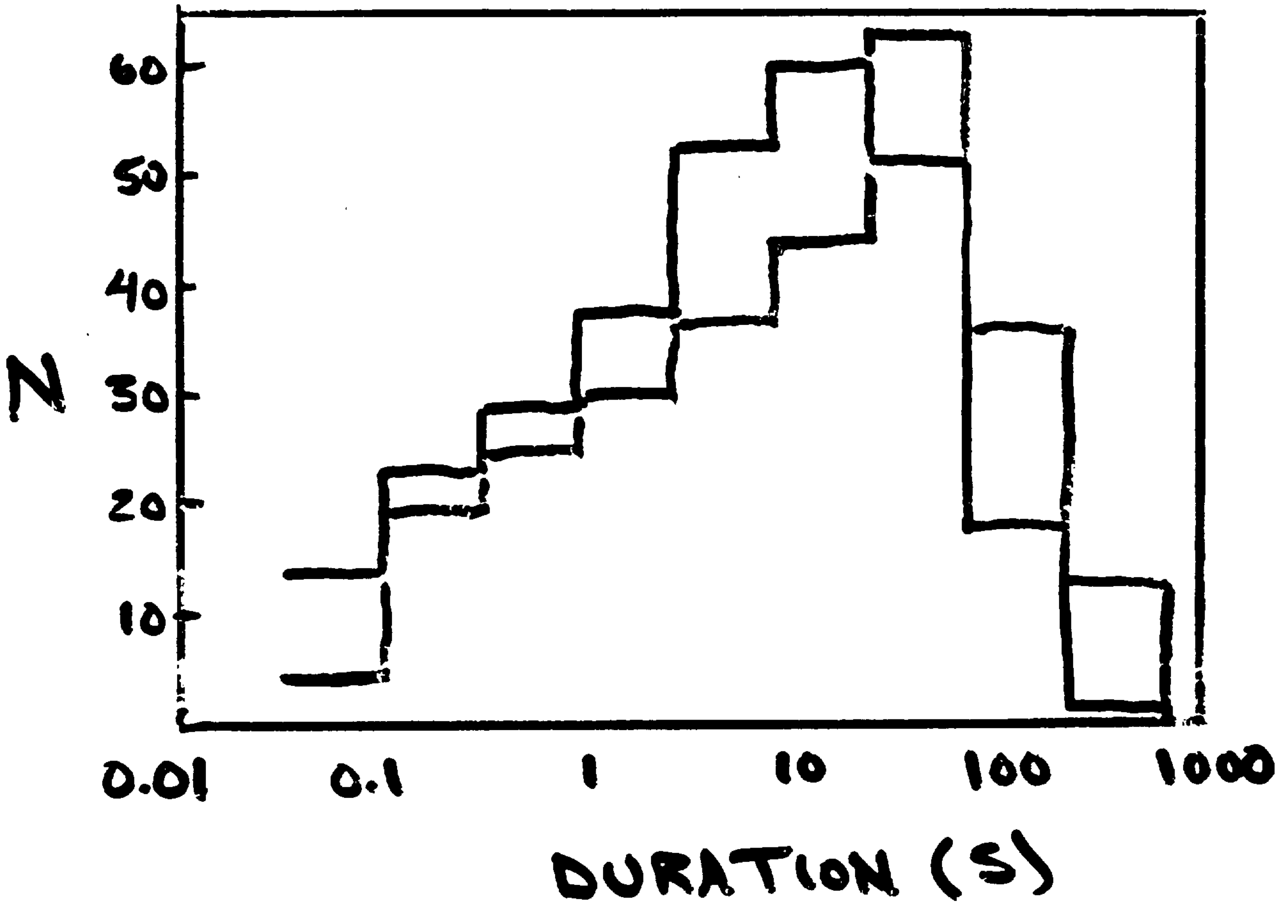
I. The Problem

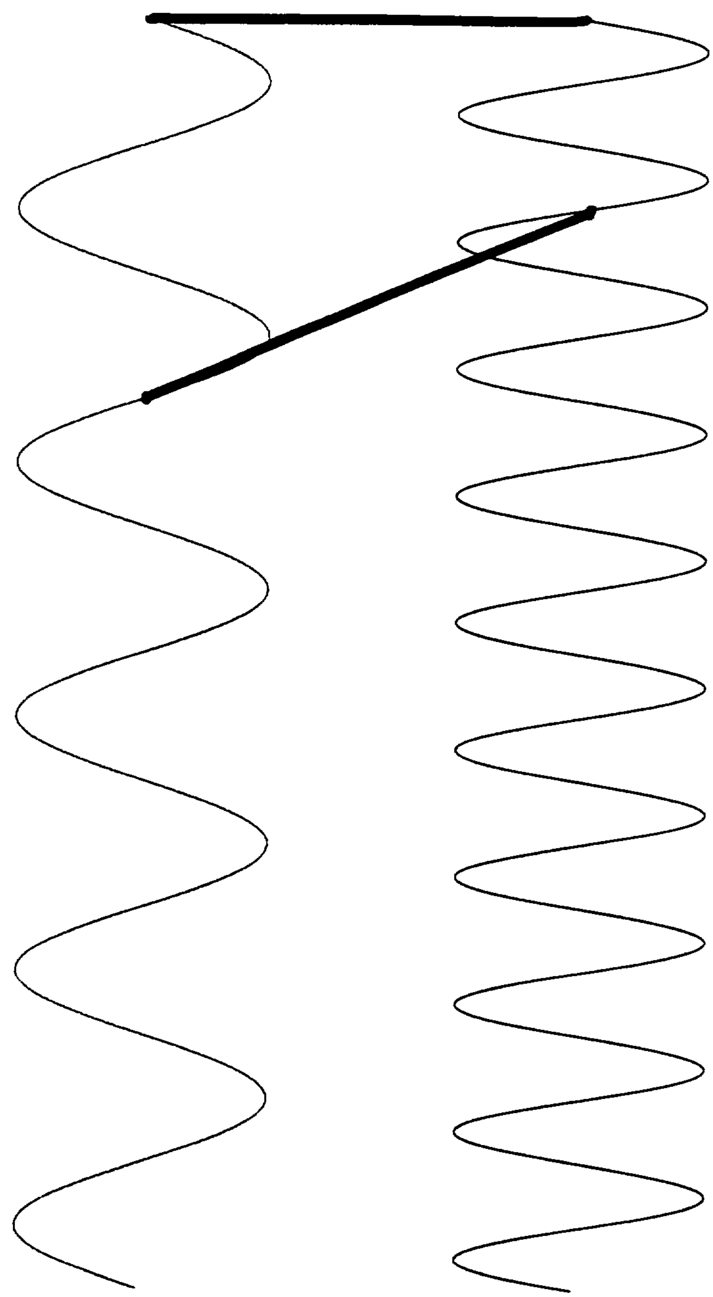
II. Measures of burst duration

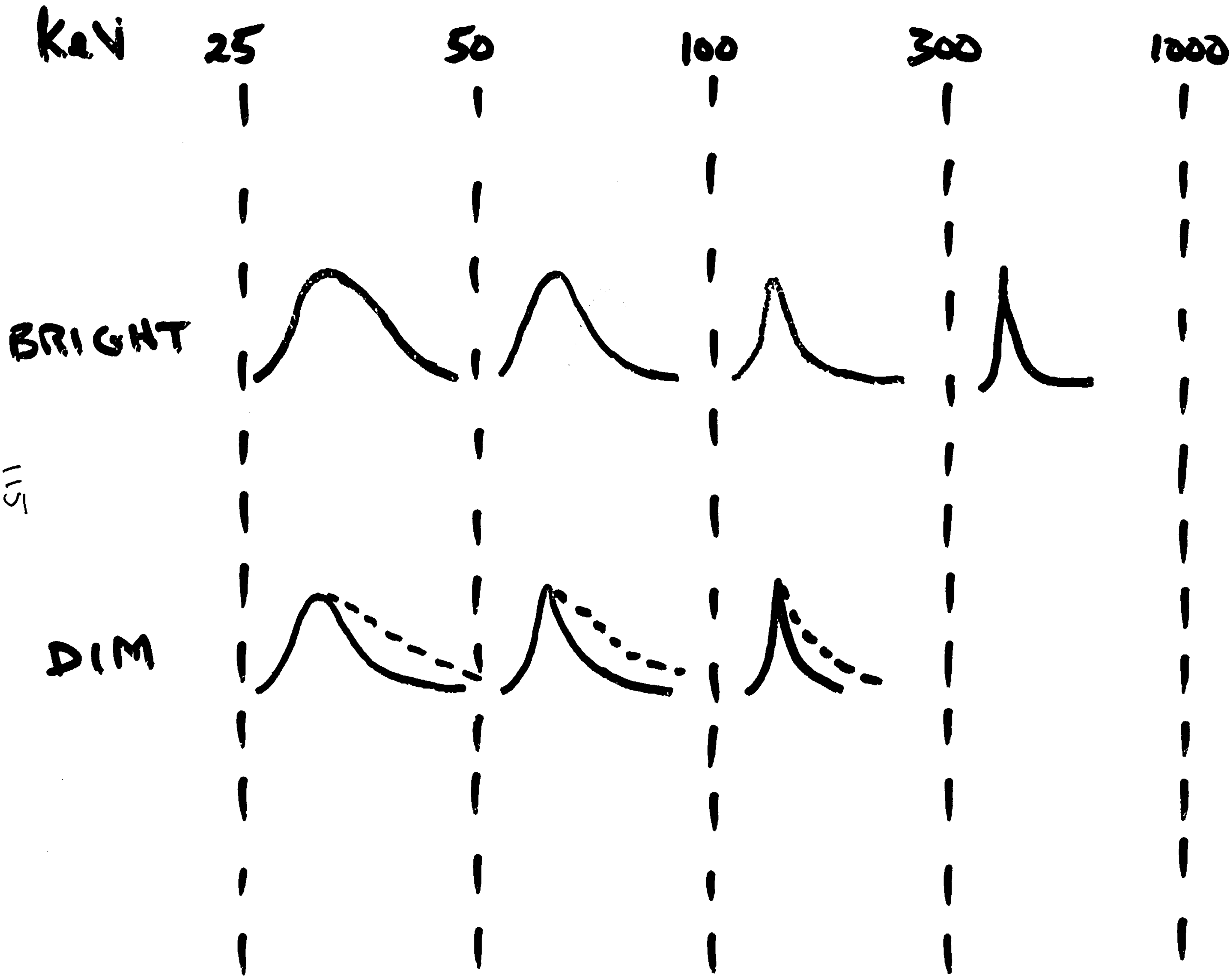
III. Brief discussion on Wavelet Transforms

IV. Applications of Wavelet Transforms to search for time dilation
- Peak Registration test
- Wavelet Decomposition test

V. Consistency check: Signatures of apparent time dilation & redshift must agree with fit to inhomogeneous source density $\Rightarrow$ Z (redshift) ~ unity.


N
60
50
40
30
20
10
0.01
0.1
1
10
100
1000
DURATION (S)




KeV
25
50
100
300
1000
BRIGHT
DIM

The Problem

If bursters are cosmological, then most distant, detected sources at redshift ~ unity
$\Rightarrow$ extremely high energy release, ~ 10^{51} ergs on time scale of seconds!

Two predicted, observable consequences:
Spectra will be redshifted,
Time profiles will be dilated
– in both cases, same factor = (1+Z)

Spectral redshift undetectable in power-law regime (> 200 keV),
but signature apparent at lower energies.

Time dilation observable, BUT complications:
wide duration distribution
pulse widths are energy-dependent $\Rightarrow$ spectral redshift moves narrower temporal structures (in source frame) to lower energies (in observed frame)

Given enough bursts, "TIME DILATION" AND "REDSHIFT" SIGNATURES MUST BE QUANTITATIVELY CONSISTENT WITH OBSERVED SPATIAL INHOMOGENEITY:
MUST FIND (1+Z) ~ 2 – else bursts aren't cosmological

Measures of burst duration, temporal structure

Interval measures (severe drawbacks: only 1 statistic per burst;
not robust over range of pulse widths)

* trigger to highest peak
* peak to end of burst ("last" significant fluctuation)
* "forward" trigger to "backward" trigger
* interval between two tallest peaks

Integral measures

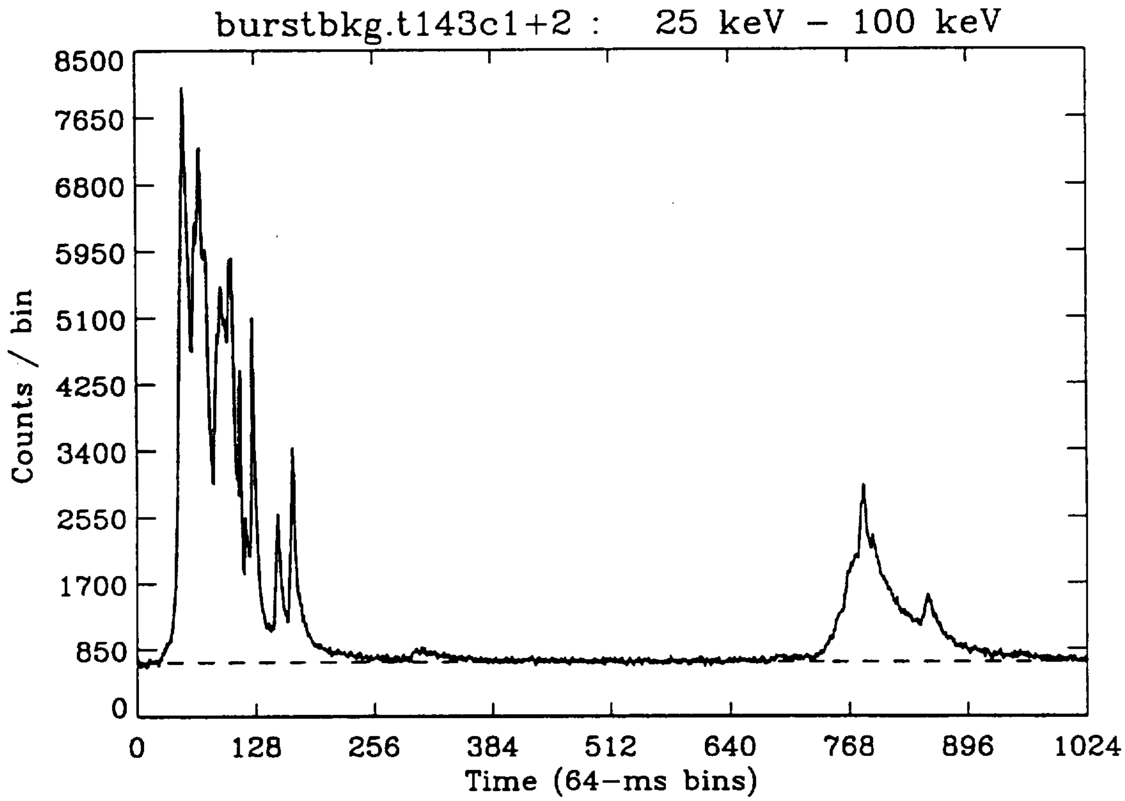
* Total counts above background in normalized burst
* Total counts within fitted pulse structures

Average profile measure: align highest peaks in registration

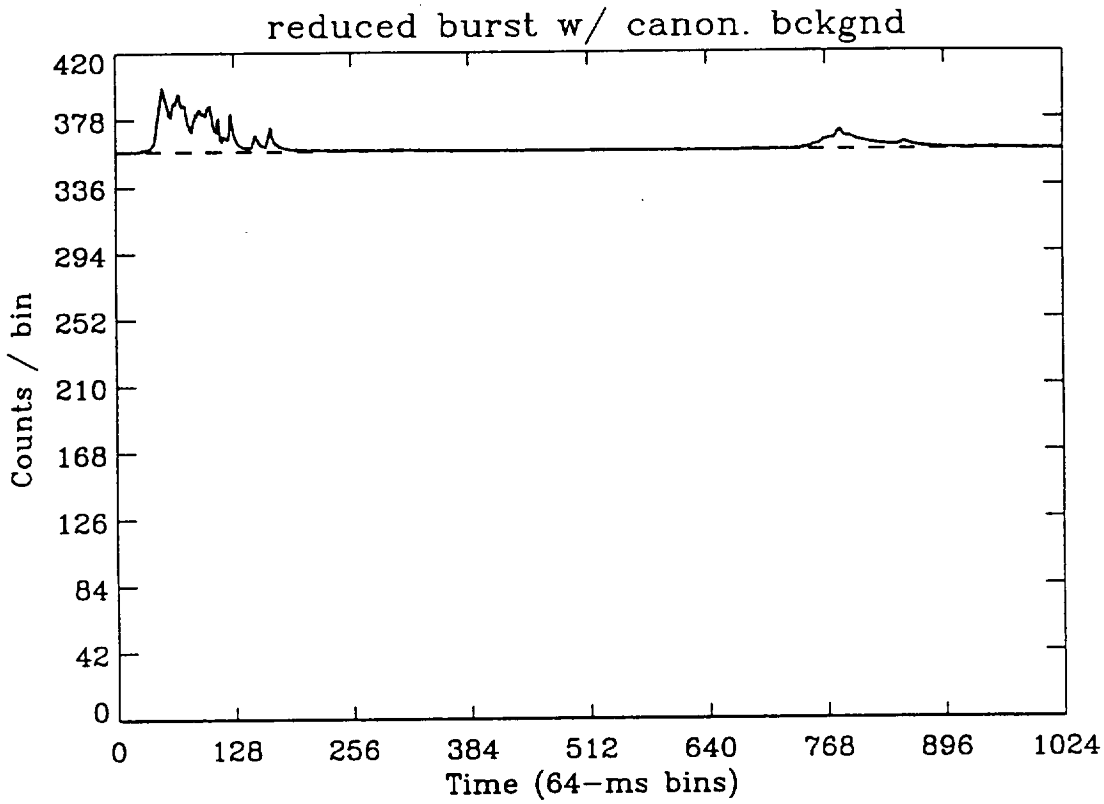
yields several statistics (core width, fwhm, e-folding rise & decay)
probes shortest time scales
uses large portion of burst profile - but usage not maximally efficient

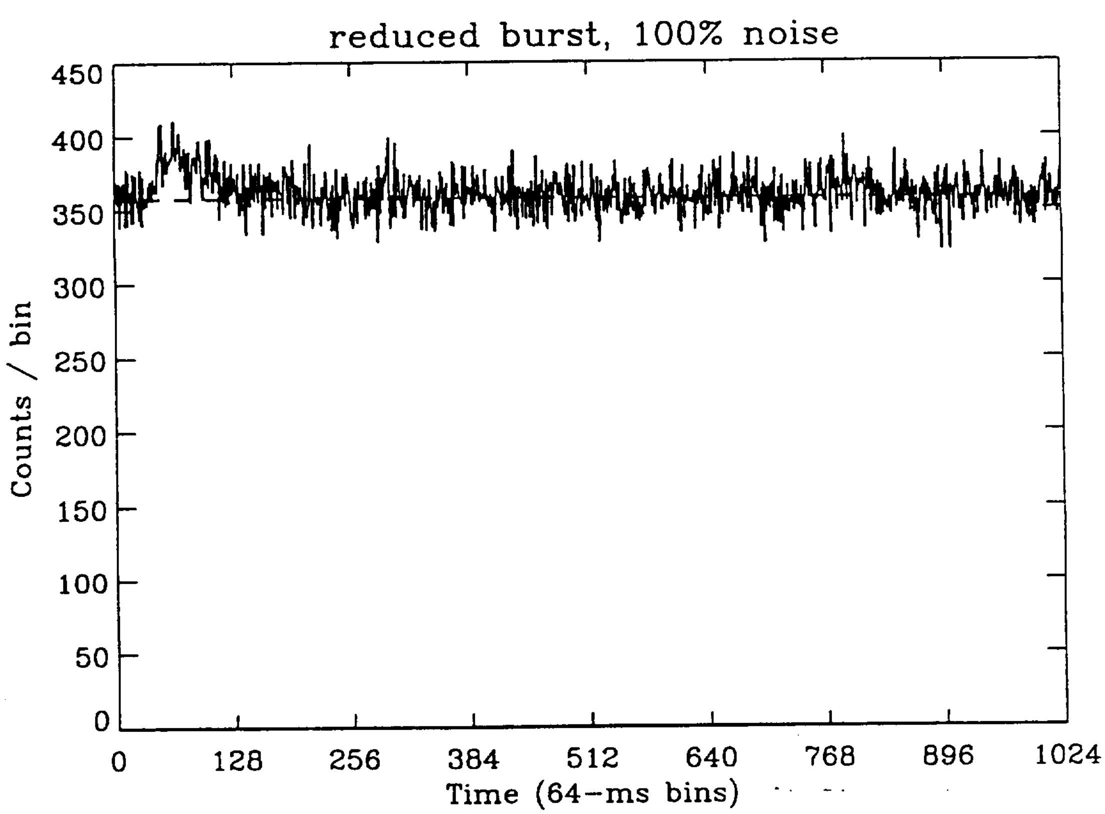
Multiresolution measures (decompose profile, analyze on range of time scales)

* Fourier transform – global basis functions (sine waves)
* Wavelet transform – local basis functions (wavelets)
* Fits to pulse structure widths; nonorthonormal



burstbkg.t143c1+2 : 25 keV - 100 keV
8500
7650
6800
5950
5100
4250
3400
2550
1700
850
0
Counts / bin
0
128
256
384
512
640
768
896
1024
Time (64-ms bins)


reduced burst w/ canon. bckgnd
Counts / bin
420
378
336
294
252
210
168
126
84
42
0
0
128
256
384
512
640
768
896
1024
Time (64–ms bins)


reduced burst, 100% noise
Counts / bin
450
400
350
300
250
200
150
100
50
0
0
128
256
384
512
640
768
896
1024
Time (64–ms bins)

"Elimination" of Brightness Selection Effects: Preparation of Time Profiles

A. Include all bursts longer than 1 s, divide into three brightness groups:

brightest	18,000	<	C_p	<	300,000	cts s^{-1}
dim	2,100	<	C_p	<	4,500	
dimmest	1,400	<	C_p	<	2,100	

Peak intensity, C_p, determined in time-scale independent manner: threshold in wavelet transform domain; only retain significant wavelets per time scale; reconstitute time profile. method preserves broad as well as narrow features.

B. Define background interval, fit with 1st order polynomial, subtract.

C. Diminish remaining "signal" profile to canonical peak intensity – that of dimmest burst used, 1400 cts s^{-1}

D. Add canonical flat background – average background for dimmest bursts. (actual backgrounds are relatively free of curvature on time scales analyzed)

E. Add empirical variance necessary to compensate for diminishing burst profile; substitute noise taken from "background" intervals of actual time profiles.

signal * shrinkfac + {empirical variance}*(1 - shrinkfac) $\Rightarrow$ 100% variance level

F. Noise in diminished burst and added substitute noise are uncorrelated. therefore, add small corrections for correlation across width scales.

G. "Retrigger" each burst, approximating actual instrument criteria.

Fourier transform: $F(\omega) = \int f(t)\, e^{-i\omega t}\, dt$

$e^{-i\omega t}$ = Fourier analyzing kernel, function of frequency

Wavelet transform: $S(b,a) = (a)^{-1/2} \int s(t)\, g\{[t-b]/a\}\, dt$

$g\{[t-b]/a\}$ = generic wavelet analyzing kernel, function of position & scale

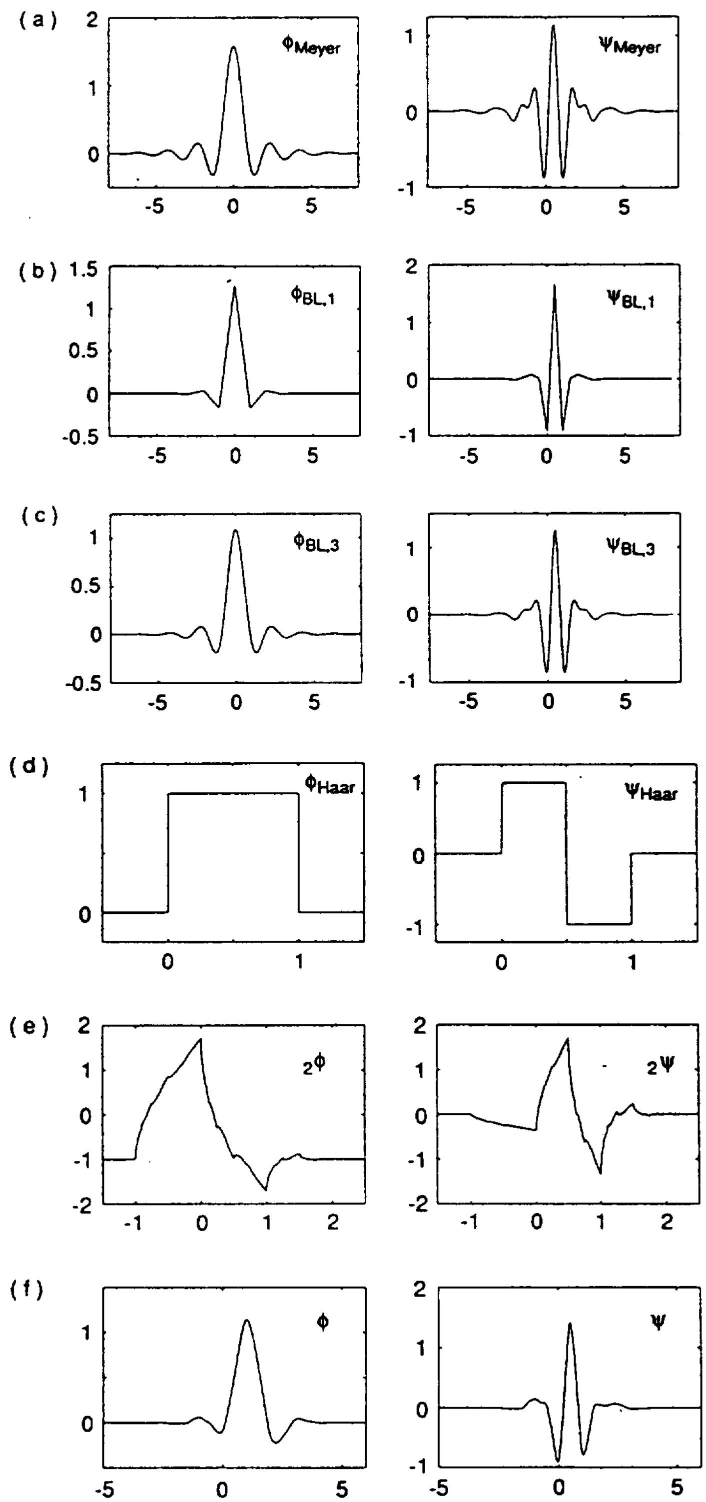


FIG. 1.8. *Some examples of orthonormal wavelet bases. For every ψ in this figure, the family $\psi_{j,k}(x) = 2^{-j/2}\psi(2^{-j}x - k)$, $j, k \in \mathbb{Z}$, constitutes an orthonormal basis of $L^2(\mathbb{R})$. The figure plots ϕ (the associated scaling function) and ψ for different constructions which we will encounter in later chapters.* (a) *The Meyer wavelets;* (b) *and* (c) *Battle–Lemarié wavelets;* (d) *the Haar wavelet;* (e) *the next member of the family of compactly supported wavelets, ${}_2\psi$;* (f) *another compactly supported wavelet, with less asymmetry.*

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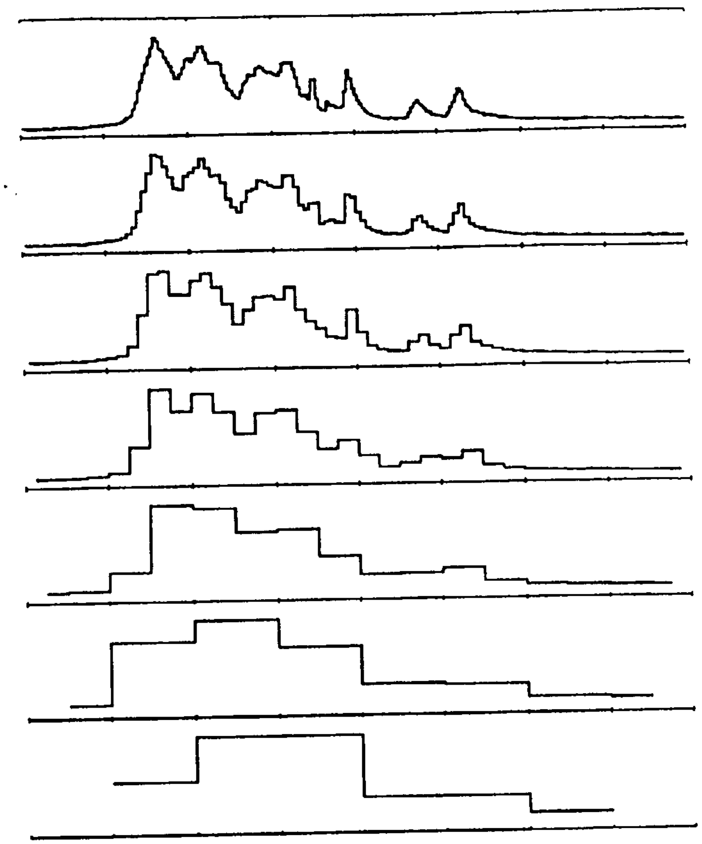
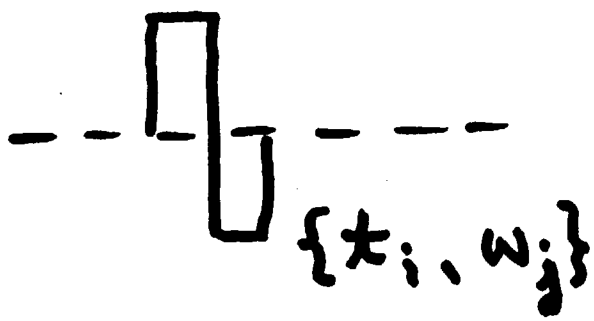
Wavelet Transforms, Pure and Simple



- * Orthonormal basis, similar to Fourier transform, except ...
- * Indexed by time scale *and* position → represents heterogeneous temporal structures parsimoniously



- * Implemented straightforwardly (for simplest wavelet):

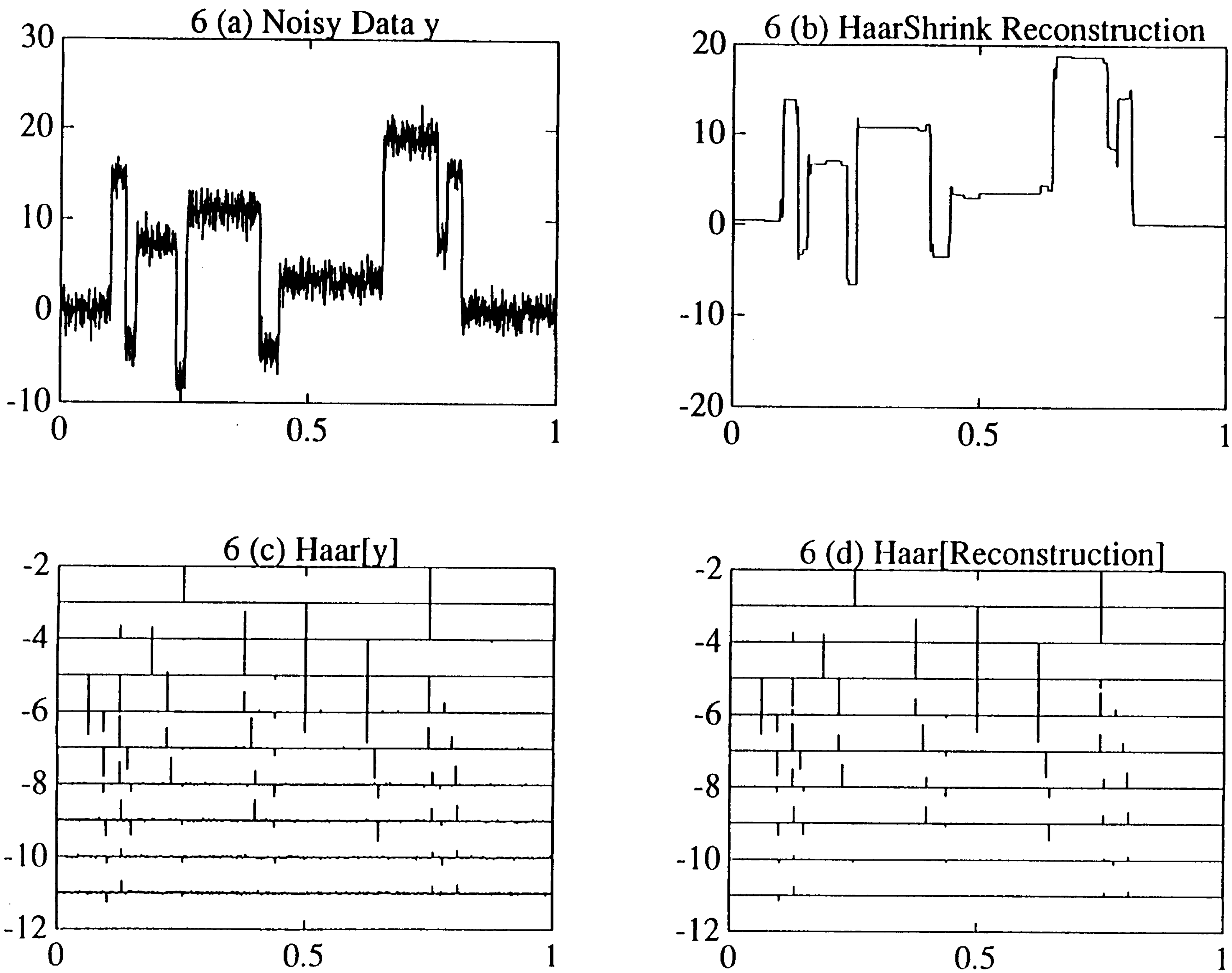
(a) differences of adjacent intensities = wavelet amplitudes

(b) bin up by factor of two, repeat step (a) to longest time scale

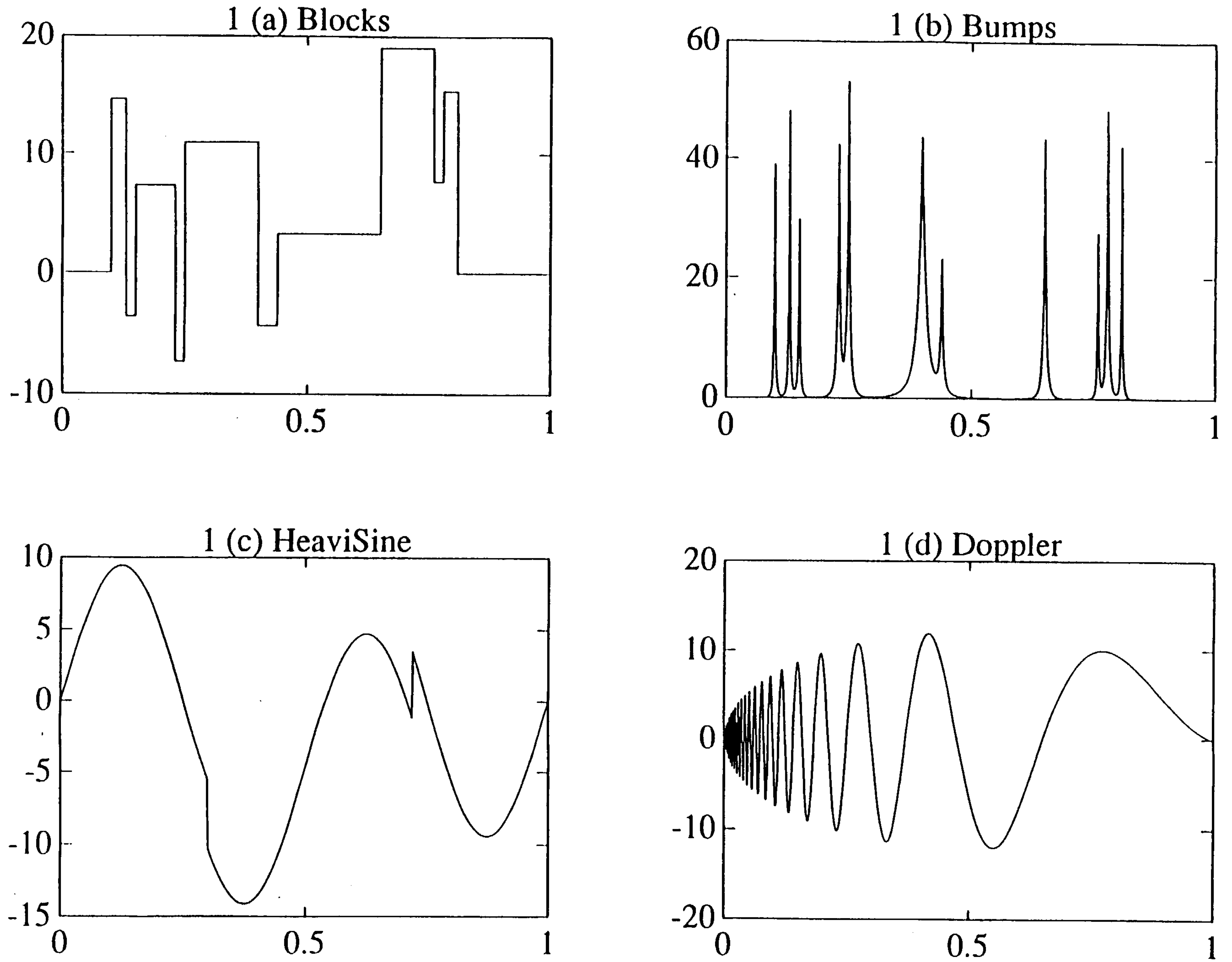
→ sets of wavelet amplitudes spanning time profile in octave steps

(c) perform Σ |amplitudes| on each octaval time scale = "activities"

DONOHO ('93)


6 (a) Noisy Data y
6 (b) HaarShrink Reconstruction
6 (c) Haar[y]
6 (d) Haar[Reconstruction]

DONOHO ('93)



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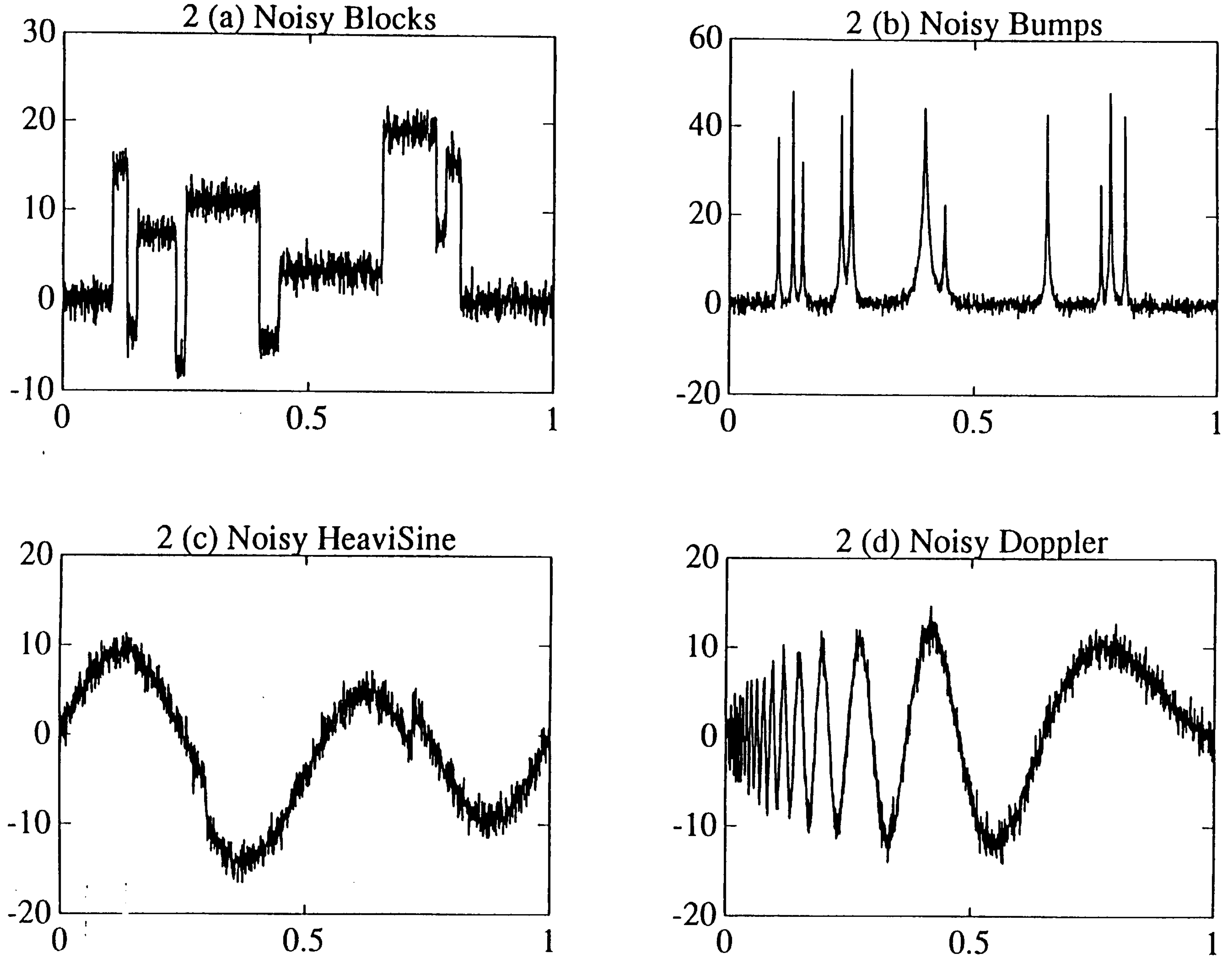
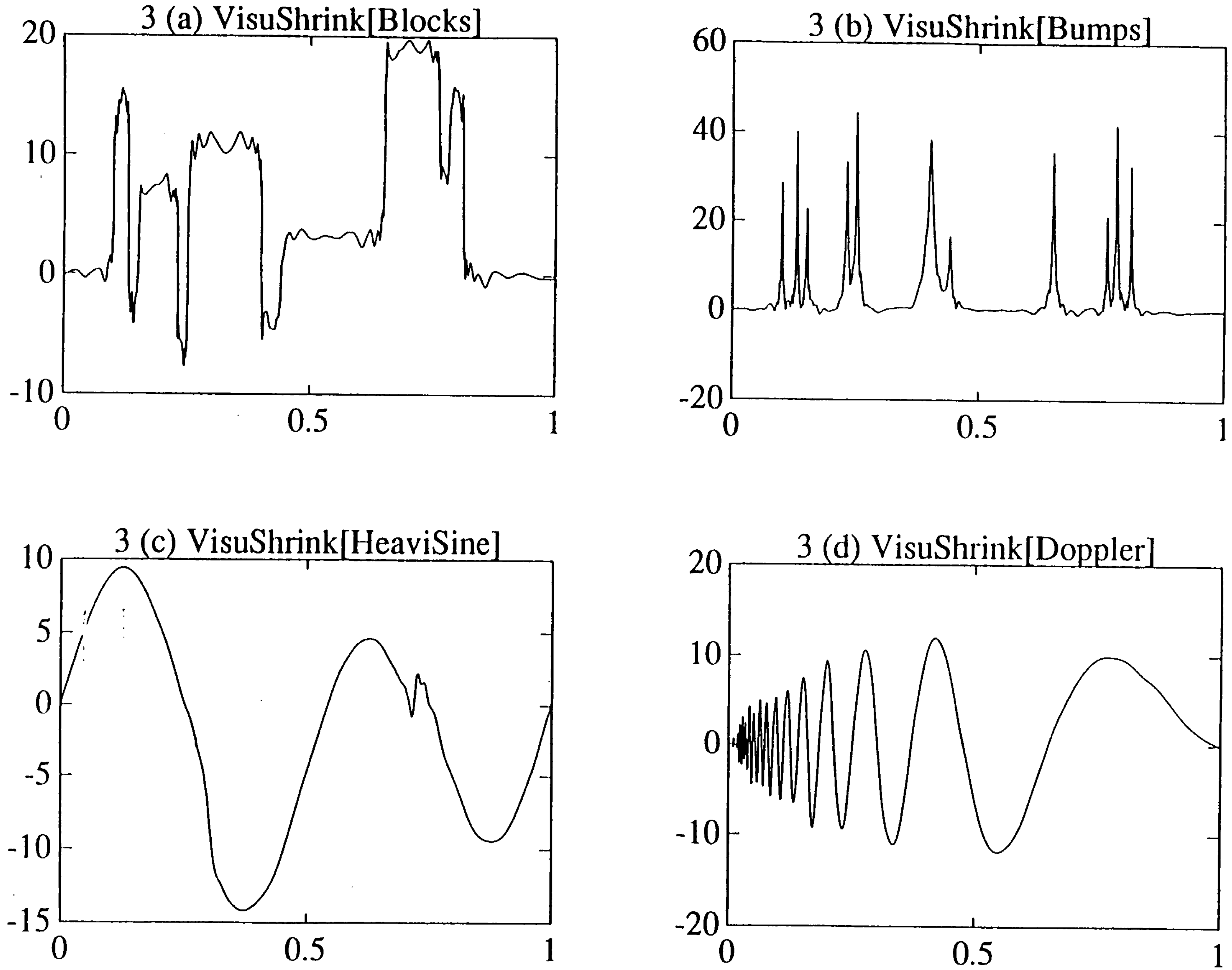
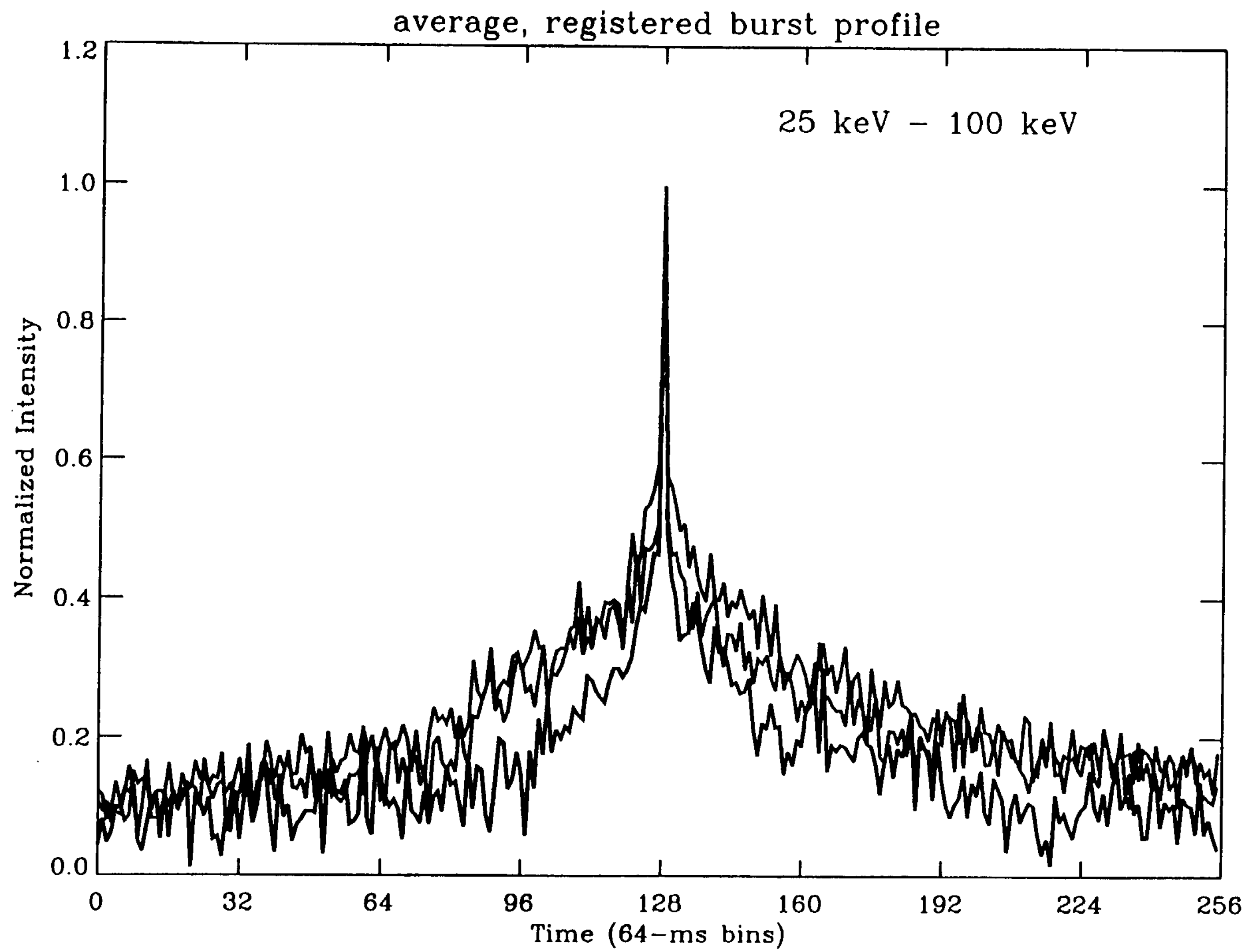
DONOHO ('93)

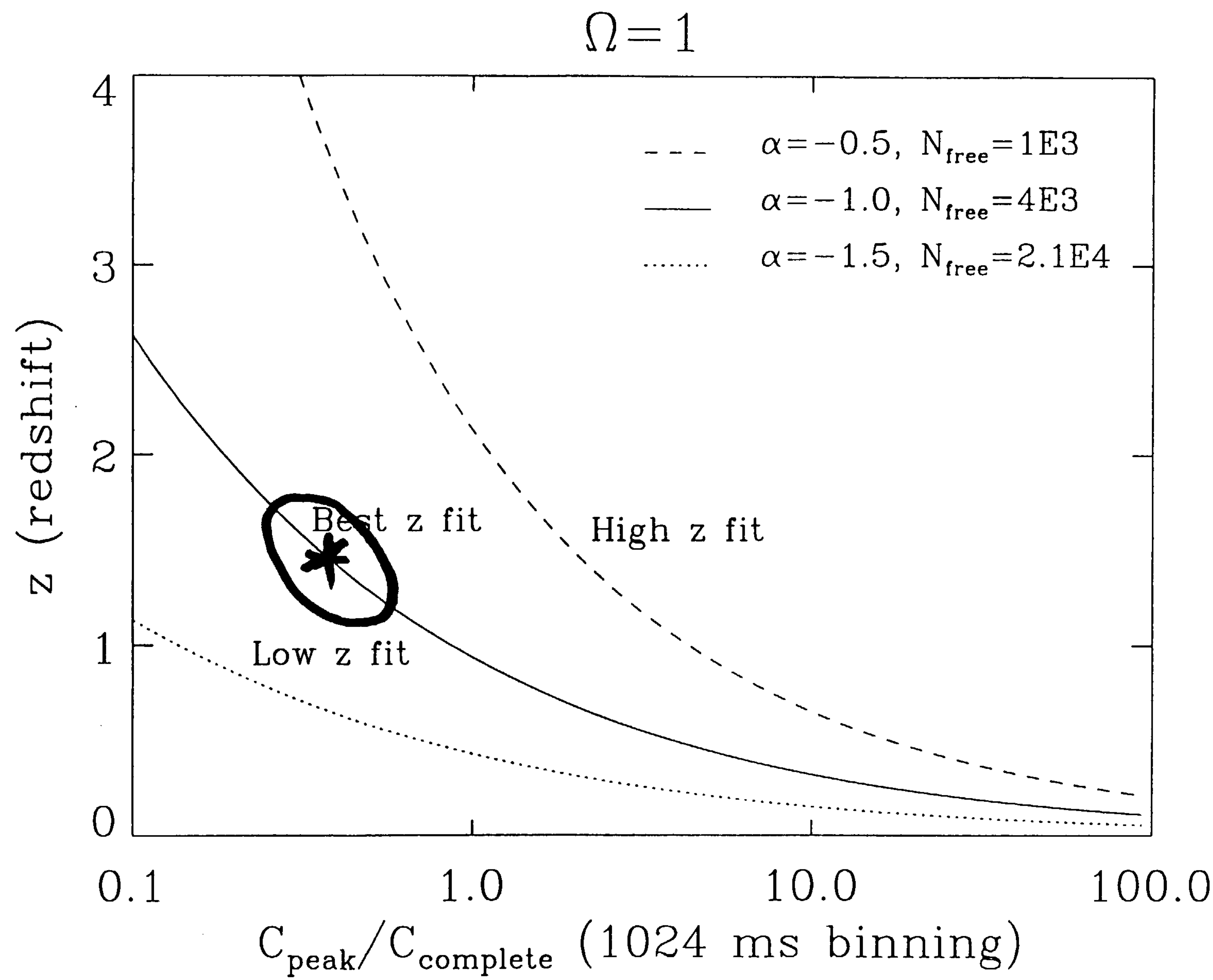


2 (a) Noisy Blocks
2 (b) Noisy Bumps
2 (c) Noisy HeaviSine
2 (d) Noisy Doppler

DONOHO ('93)


3 (a) VisuShrink[Blocks]
3 (b) VisuShrink[Bumps]
3 (c) VisuShrink[HeaviSine]
3 (d) VisuShrink[Doppler]
20
10
0
-10
60
40
-20
5
-5
-15
0.5
1


average, registered burst profile
25 keV - 100 keV
Normalized Intensity
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0
32
64
96
128
160
192
224
256
Time (64-ms bins)



$\Omega=1$
$\alpha=-0.5,\ N_{free}=1E3$
$\alpha=-1.0,\ N_{free}=4E3$
$\alpha=-1.5,\ N_{free}=2.1E4$
Best z fit
High z fit
Low z fit
z (redshift)
$C_{peak}/C_{complete}$ (1024 ms binning)
0.1
1.0
10.0
100.0
0
1
2
3
4

Are GRBs Cosmological ?

* Measurements of "stretch" factor, $[\langle\tau_{dim}\rangle/\langle\tau_{brt}\rangle]_{w(j)}$, agree within errors
  – across seven octaves in temporal structure width: $[\langle\tau_{dim}\rangle/\langle\tau_{brt}\rangle]_{w(j)} \approx 2$.
* Dim bursts look "softer" (redshifted).
* Isotropic celestial distribution, sampled to "edge".
* BUT?! 10^{51} ergs per event ?? Event density ~ 5 bursts Gpc^{-3} yr^{-1} (no repeats).

What else needs to be done:

Correct apparent time dilation measurements for energy-dependent redshift effect (pulse narrowing at higher energies), ~ 15% effect.

Quantify correlation of peak intensity with softness - is "redshift" of dim bursts same factor of two ?

Better background subtraction - enables analysis over longer intervals.

Explore other (nonorthonormal?) wavelet bases for characterizing time profiles.

Search for gravitational lensing of bursts.

Fly experiment to look for soft X-ray absorption in plane of galaxy - should be latitude & longitude dependent.

Kinematic vs. Cosmological Time Dilation

The redshifting of galaxies is the result of the mathematics that define Friedman Robertson Walker (FRW) cosmologies. One can interpret this redshift wholly kinematically as the recession velocities of galaxies, but this picture is incomplete. In a real sense, however, these galaxies are moving away from us – you can fit more and more meter sticks between us and them as time goes by. These galaxies, however, live in a younger denser universe, where time runs slower, and light must climb out of a gravititation well to get from them to us – all of which gets convolved into the one measurement we call redshift.

If one were to hypothesize a completely Newtonian (but special relativistic) universe where recession velocity was all there was, one would find that this universe contains paradoxes that are not well explained (for example: gravitational collapse calculations assume no mass at infinity – which is not upheld in this Newtonian + SR universe). Einstein found the best way yet to staple gravity and SR together – (it took him years and many false starts) and the result was GR and the immediate result of that was FRW cosmologies. Can anyone completely visualize the reasons for GR and FRW cosmology? – not completely. As R. Feynman once said – there is no complete understanding of gravity beyond the mathematical form.

But even if GR is wrong and recessional velocity reigns supreme, you would STILL get a time dilation. In this case it is just the Doppler shift of a recessional velocity. In my opinion, time dilation is based on more sound measurements (QSO redshifts of spectral lines, for example) than the whole of GR theory itself. Our measurement of time dilation is, however, the first explicit measurement of this dilation, as the others are all based on spectral lines.

– Bob (Nemiroff)

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The Catholic University of America

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Jeff Scargle
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Jerry Fishman, Chip Meegan, Bob Wilson, Brad Rubin, Jeff Pendleton
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References

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   monograph, formal wavelet theory

2. "Wavelets, Time-Frequency Methods and Phase Space," eds. J.M. Combes, A. Grossman & Ph. Tchamitchian (Springer-Verlag: New York, 1987).
   31 contributions, many application-oriented

3. IEEE Trans. Information Theory, Vol 38, No 2, 1992 (special issue on wavelets).
   32 articles, current developments in theory and application

4. I. Daubechies, "The Wavelet Transform, Time-Frequency Localization, and Signal Analysis", IEEE Trans. Information Theory, Vol 36, No 5, p. 961, 1990.
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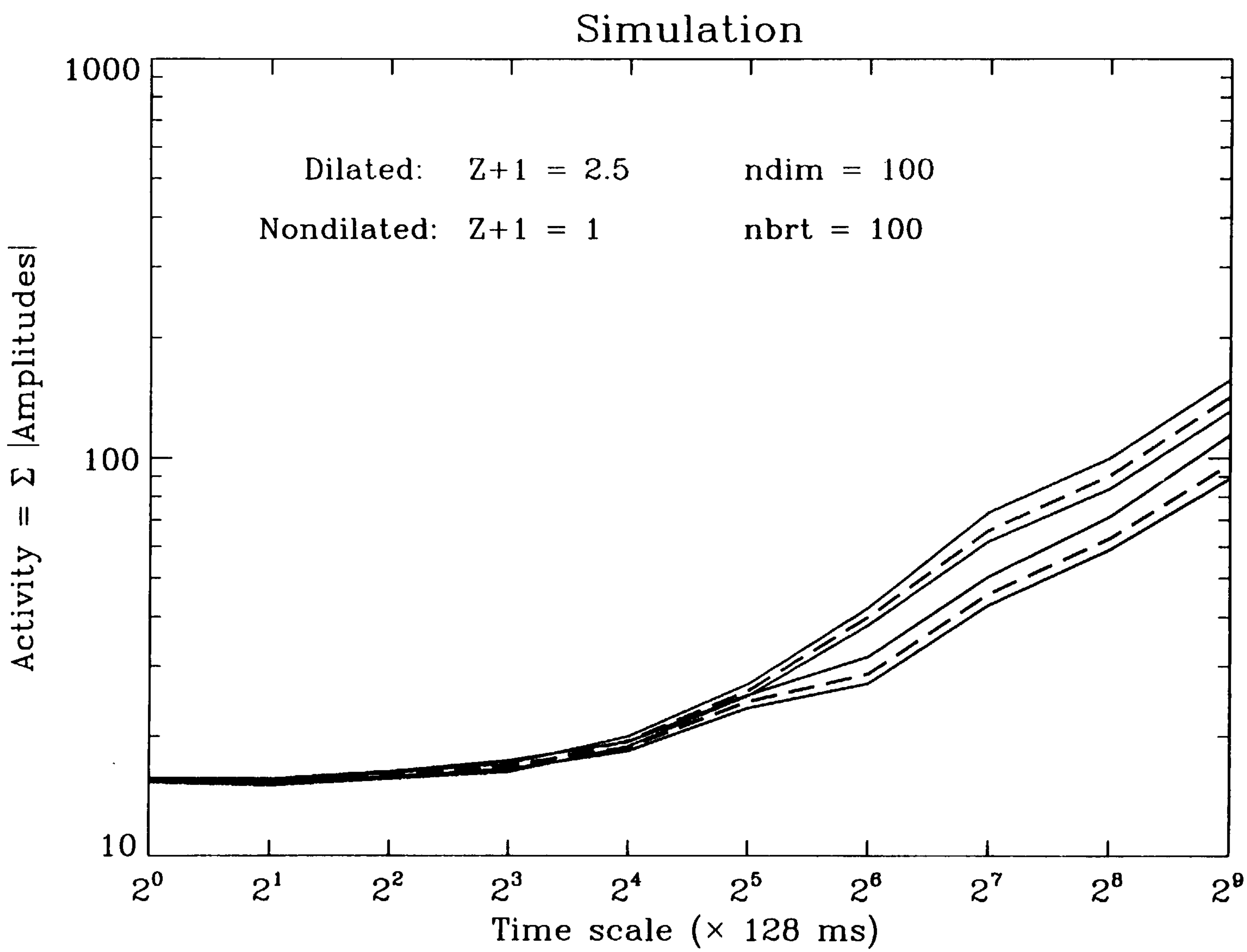
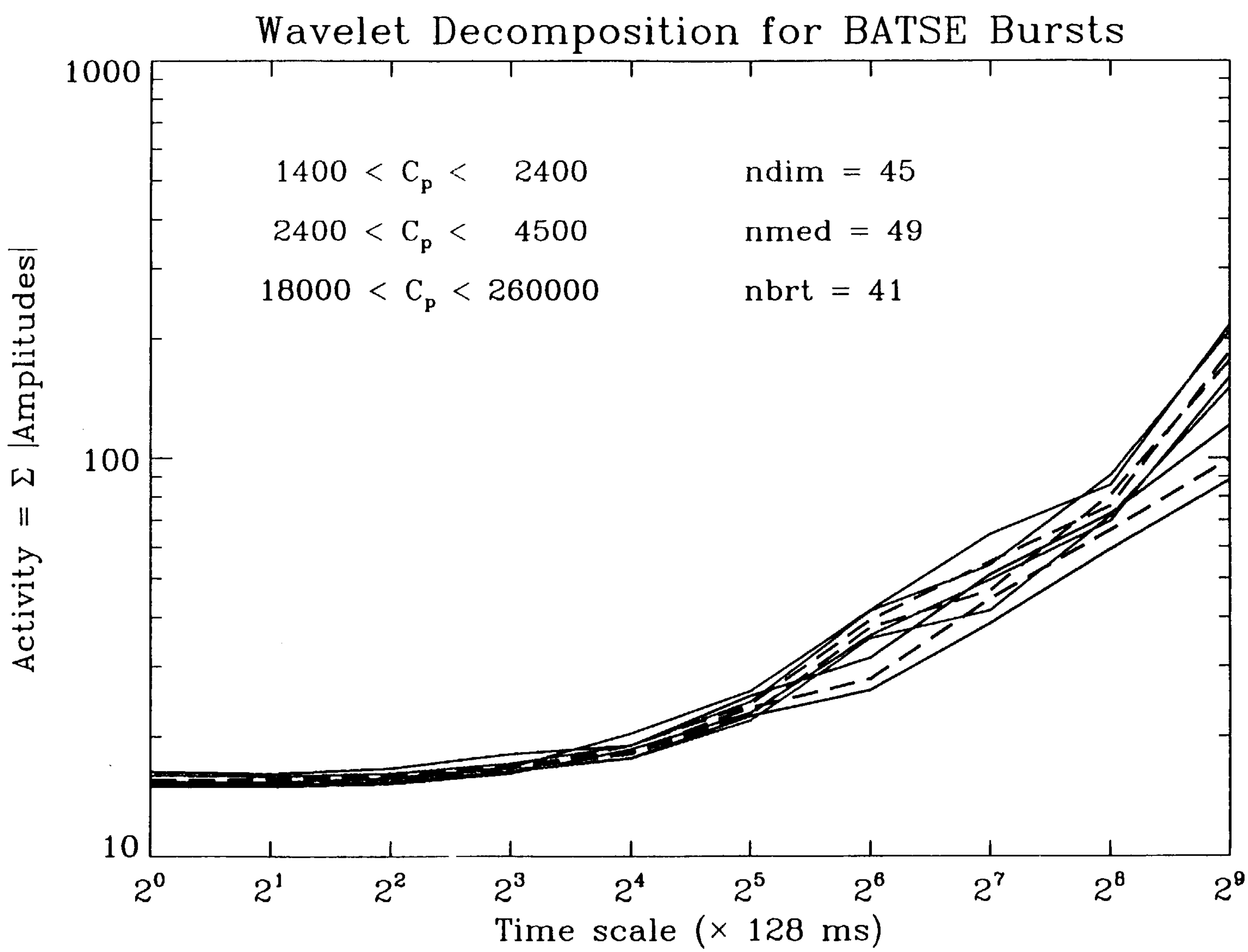
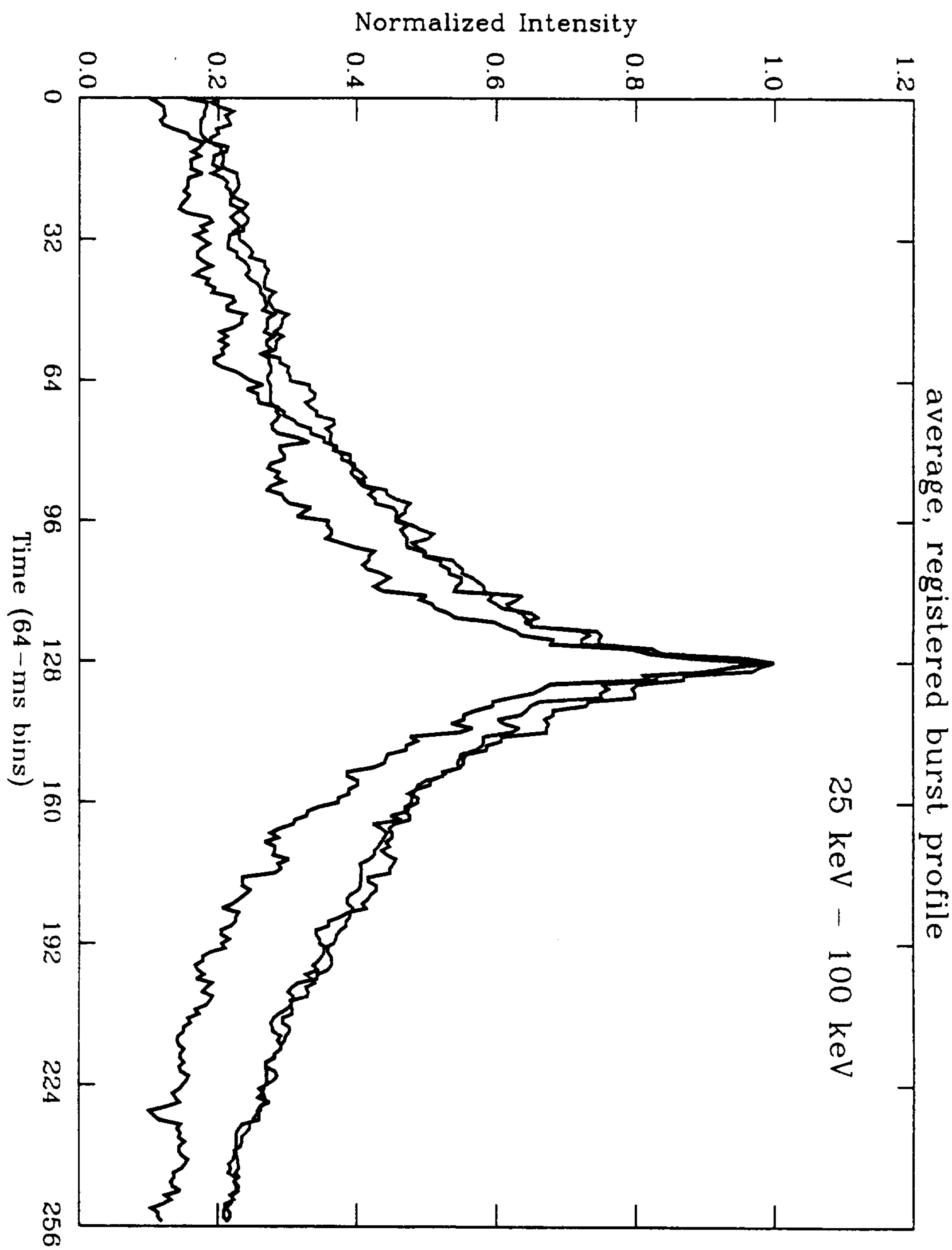
5. D. Donoho, "Wavelet Shrinkage and W.V.D.: A 10-Minute Tour", Tech. Report #416, Stanford University, 1993.
   time-scale independent noise reduction via wavelet thresholding

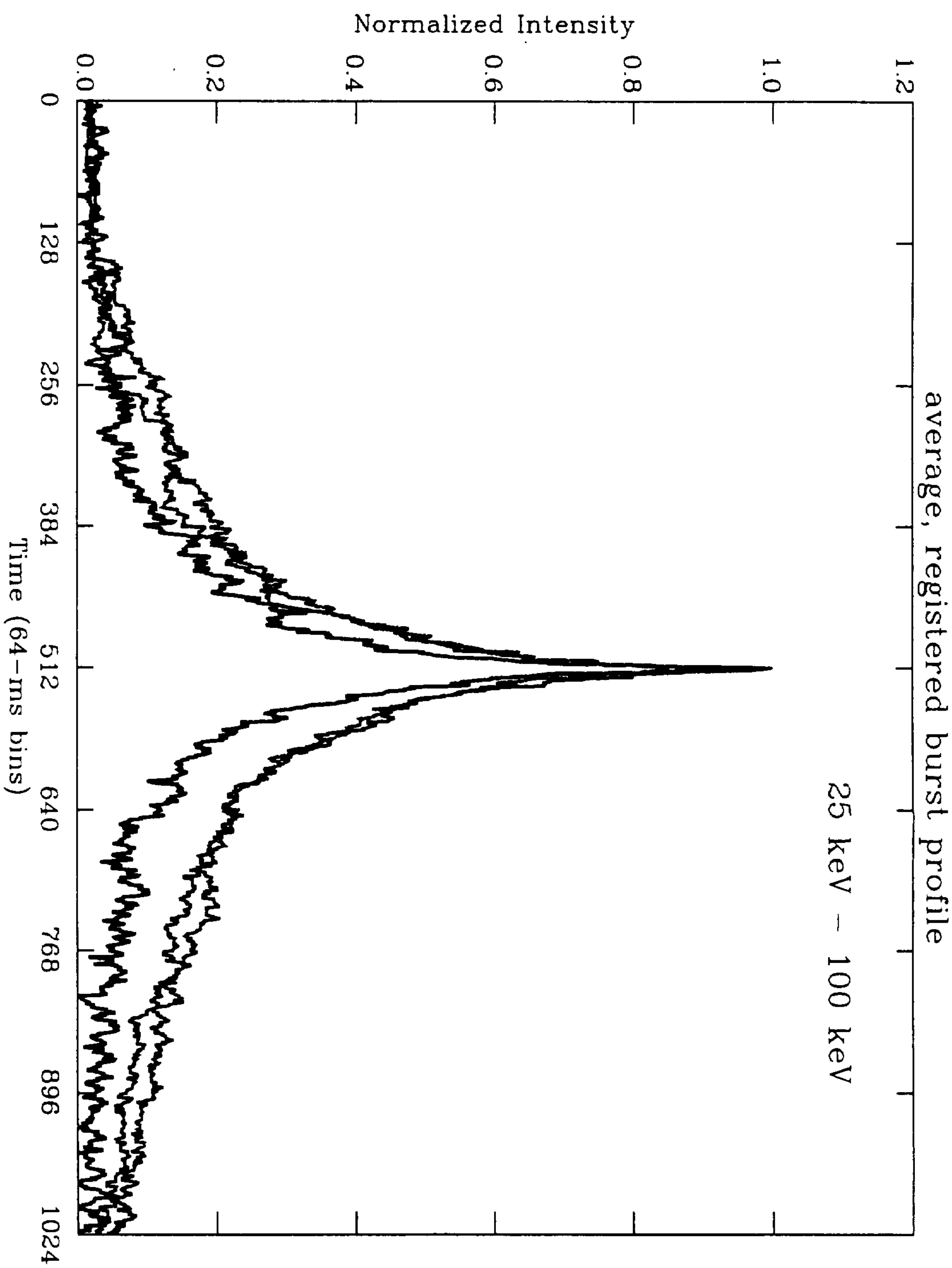
6. "Gamma-Ray Bursts," AIP Conference Proceedings 265, eds. W.S. Paciesas & G.J. Fishman, 1991.
   77 articles on gamma-ray burst observations, theory, and instrumentation

7. Proceedings of the *Compton* Symposium, AIP, eds. N. Gehrels, M. Friedlander & D. Macomb, 1993, in press.
   over 200 articles on gamma-ray astrophysics

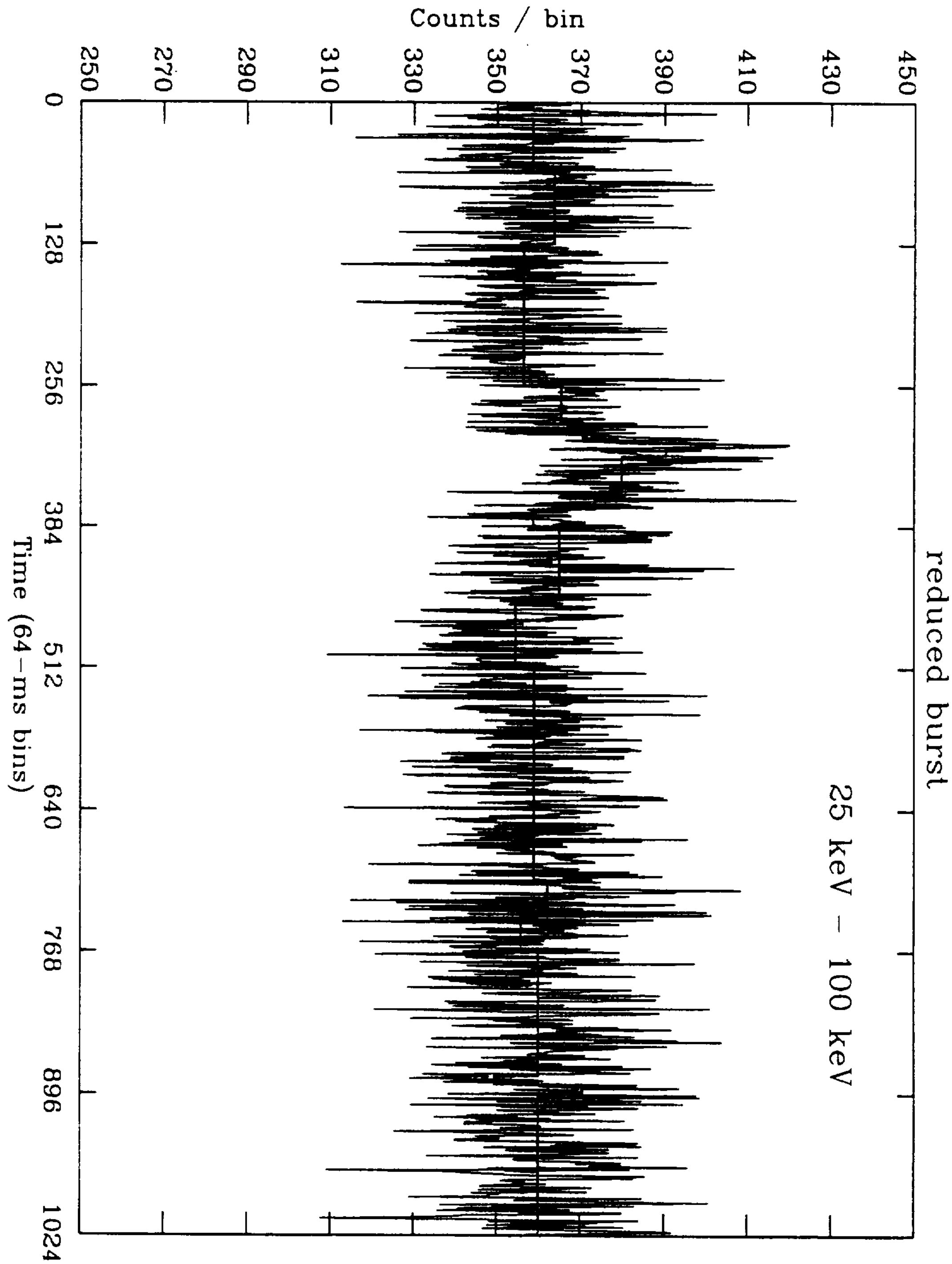

Simulation
Dilated: Z+1 = 2.5 ndim = 100
Nondilated: Z+1 = 1 nbrt = 100
Activity = Σ |Amplitudes|
1000
100
10
2⁰ 2¹ 2² 2³ 2⁴ 2⁵ 2⁶ 2⁷ 2⁸ 2⁹
Time scale (× 128 ms)

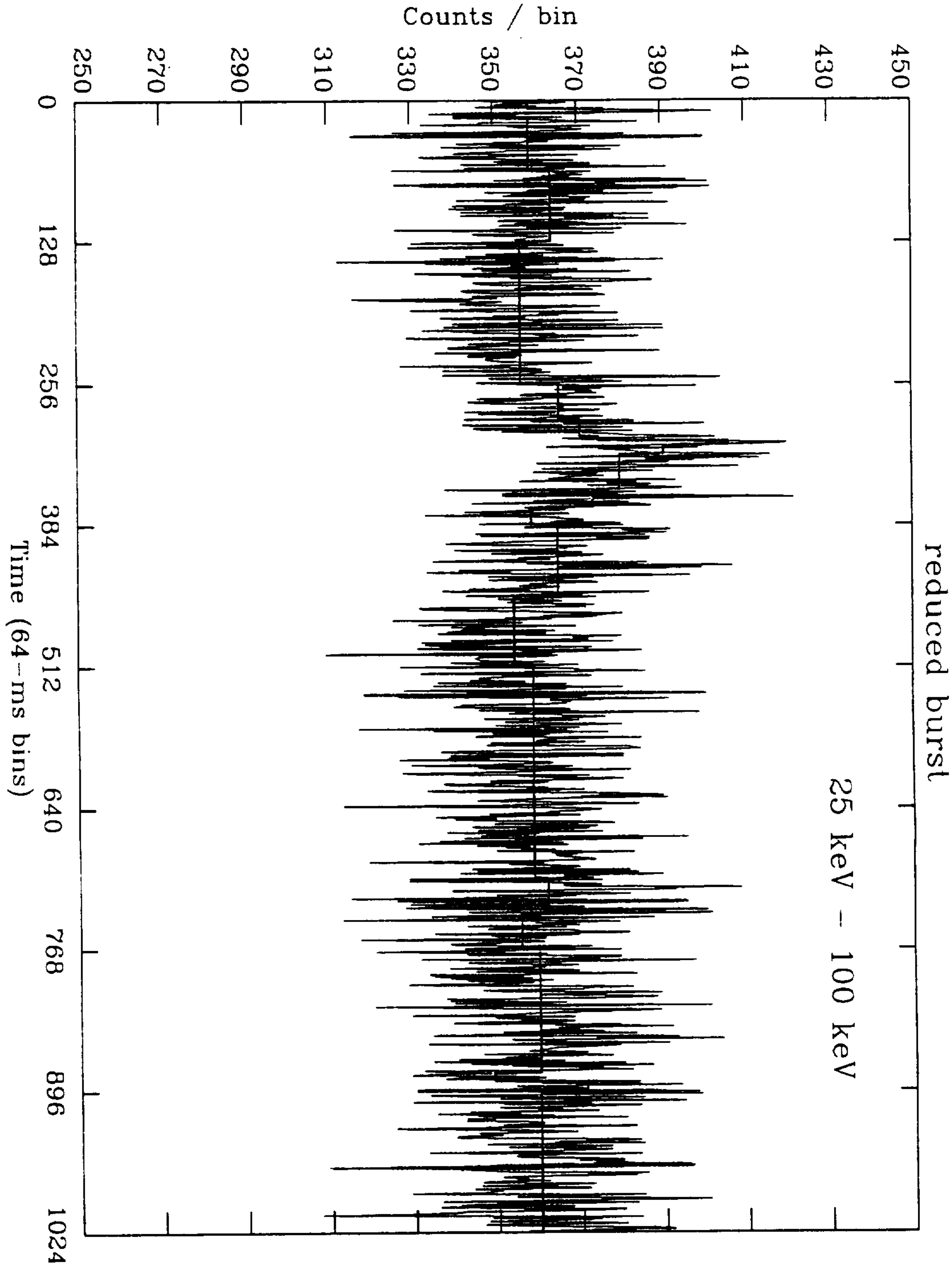

Wavelet Decomposition for BATSE Bursts
1400 < C_p < 2400
ndim = 45
2400 < C_p < 4500
nmed = 49
18000 < C_p < 260000
nbrt = 41
Activity = Σ |Amplitudes|
1000
100
10
2^0
2^1
2^2
2^3
2^4
2^5
2^6
2^7
2^8
2^9
Time scale (× 128 ms)


average, registered burst profile
25 keV – 100 keV
Normalized Intensity
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Time (64–ms bins)
0
32
64
96
128
160
192
224
256



average, registered burst profile
25 keV – 100 keV
Normalized Intensity
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0
128
256
384
512
640
768
896
1024
Time (64-ms bins)


Counts / bin
250
270
290
310
330
350
370
390
410
430
450
0
128
256
384
512
640
768
896
1024
Time (64-ms bins)
reduced burst
25 keV - 100 keV


reduced burst
25 keV – 100 keV
Counts / bin
250
270
290
310
330
350
370
390
410
430
450
0
128
256
384
512
640
768
896
1024
Time (64-ms bins)

Concept Formation in Temporally Structured Domains

Wayne Iba

April 8, 1993

Introduction

Unsupervised learning, or *concept formation*, is an important area of machine learning. In this work, *unlabeled* data is presented to a concept formation system, and the system must form concepts, or classes, that best characterize the observed data. Although unsupervised learning mechanisms do not require class labels, many of these methods have been successfully applied to supervised learning tasks. In general, the concept formation system can take advantage of a class label when it is available, but is not dependent on the presence of such a label.

Most previous concept formation systems have been designed to address data and domains where instances are represented as a simple set of attribute-value pairs. However, many domains of practical interest contain relationships – particularly temporal relationships. Such *temporally structured* domains require special techniques to form useful concepts from unlabeled data. We have developed OXBOW, an unsupervised learning system that addresses domains where time, or change, is a critical characteristic.

Summary of the Approach

The approach adopted in OXBOW assumes that instances consist of a series of state descriptions over time, where each state description is represented in the traditional form (i.e., a set of attribute-value pairs). The system consists of two separate modules, a parser and a classifier. The parser takes the time-sequence of attribute values and finds significant *break points* as indicated by discontinuities in the first or second derivatives of an attribute. The output of the parser is usually a subsequence of the states present in the input, but where the states correspond to the changes observed in the temporal data.

This parsed structure is then processed by the classifier. The job of the classifier is to identify the best match of this instance to the classes it has constructed from all previous data. Intuitively, the sequence of significant states should be characteristic of similar instances observed in the past, and should guide the system to select the appropriate concept. In addition to finding the best match, the classifier must also determine how to update its knowledge base in response to the current data. In some cases, such as when a previously unobserved event has been presented, the system must decide to create an entirely new class of unlabeled events. That is, in order to maintain high classification accuracy, the classifier must continually update its knowledge in response to newly acquired data. The evaluation function used to guide OXBOW to a useful set of concepts and to the "best" match for a test instance is based on Gluck and Corter's *category utility* measure and attempts to trade off the ability of a class to predict any particular attribute, and the ability of any given attribute to predict the class.

Evaluation Methodology and Results

We developed and extensively tested an earlier version of OXBOW in the domain of recognizing jointed limb movements and handwritten letters. A new version has been implemented for recognizing the initiation of events on the shuttle's power bus. The previous results on recognizing handwritten letters were quite encouraging and preliminary results on the power bus domain appear positive as well.

Experimental design

Our first empirical evaluation of the revised OXBOW used a set of 36 signatures characterizing electrical events on a three-phase power bus from shuttle telemetry. The 36 signatures were selected from the startup events of six different components on the shuttle. However, the number of examples of each type were not uniform; one of the signature types had only three examples and the most frequent had eight. A signature for an event consists of current data (measured in amps) for the three electrical phases during the initial six seconds of a component's operation.

This experiment ignored each signature's type for purposes of classification, and used it only for evaluation purposes. We performed a cross-validation study with this data set by training the system on 35 of the signatures and testing OXBOW's classification on the remaining signature. We did this for each of the 36 signatures so that every signature was individually removed from the training set and tested in turn. The training set of 35 signatures was randomly sampled without replacement during learning. We determined the accuracy of a signature's classification by comparing its type to the set of signature types stored at the concept in memory where OXBOW would have stored the test signature. The fraction of signatures whose types matched the test instance was used as the accuracy score. So, we maintained information about the signature types even though the learning system did not have access to this information.

Preliminary results

The results indicate an average classification accuracy of 91.7% (three mis-classifications) over this data set. This experiment used all six seconds of data from each signature. In a second experiment, we used a shorter portion of each signature during training and testing by trimming the set of signatures to an average length of 0.975 seconds. (The details of our trimming method are beyond the present scope.)

A similar cross-validation study showed classification accuracy to fall to 70.7% in this condition where less data was used. For our data set, the strategy of guessing the most frequent signature would yield 22% accuracy. Although overall accuracy was significantly lower, this second condition revealed that OXBOW could frequently make accurate classifications using relatively little data. We expect that these preliminary results represent lower bounds as we make modifications to the system so that it will include the signature type information during training. There are several other modifications that can be made to tune OXBOW more carefully to this domain.

Conclusion

There are three primary areas of promise for OXBOW. First, it is especially useful in domains where an unknown and potentially large number of different concepts must be discriminated. Second, the system can accomplish this task even when a small percentage of the data is actually labeled. Last, OXBOW provides a relatively general mechanism that can function effectively in many different temporally structured domains. On the down side, this approach is rather expensive computationally, and the final predictive accuracy may not exceed that of a special purpose approach. However, all results to date have suggested that OXBOW could play an integral role in temporal recognition tasks.

Concept Formation in Temporally Structured Domains

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Thanks to:
Kevin Thompson
John Allen
Phil Laird
Ron Saul

Introduction

What is the problem?

Accurately classify temporal events of interest based on previous exposure to similar events

What is the approach?

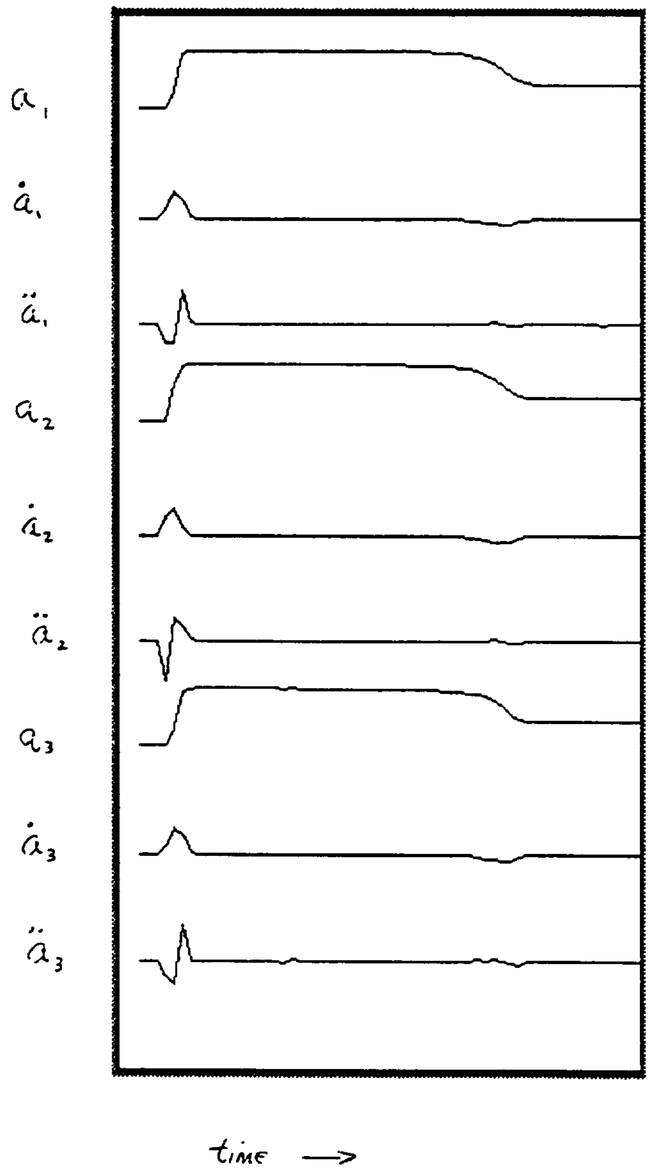
Concept formation – the incremental unsupervised acquisition of a classification scheme over a data stream

- why unsupervised learning?

What is accomplished?

Promising classification accuracy without supervised training

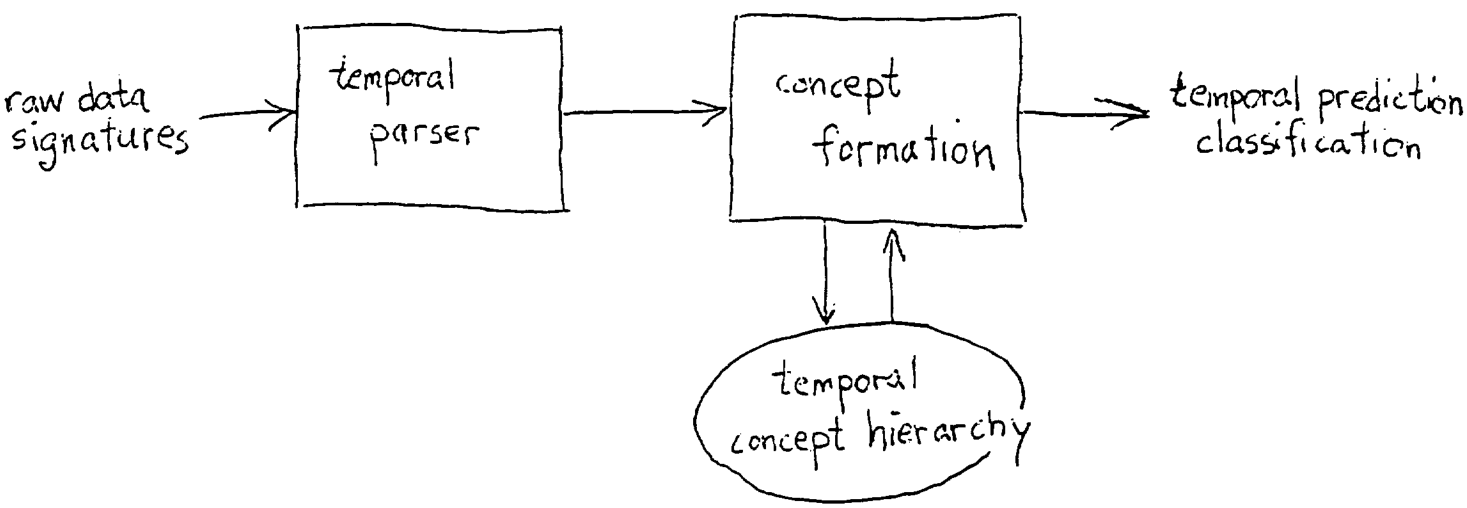
A Sample Signature



The Oxbow System

We developed Oxbow to represent, acquire, and recognize classes of jointed limb movements.

- extended to generic temporal event recognition



Parsing Temporal Events with OXBOW

Input format:

$$((t_1, \mathbf{A}_1), (t_2, \mathbf{A}_2), \ldots, (t_n, \mathbf{A}_n))$$

where

$$\mathbf{A}_i = [att_1, att_2, \ldots, att_k]$$

The parser extracts first and second derivatives for the attributes and creates sequence states according to zero-crossings detected.

Parsed output format:

$$((t_1, \mathbf{A}_1, \dot{\mathbf{A}}_1), \ldots, (t_j, \mathbf{A}_j, \dot{\mathbf{A}}_j))$$

for $j \ll n$

Concept Formation with OXBOW

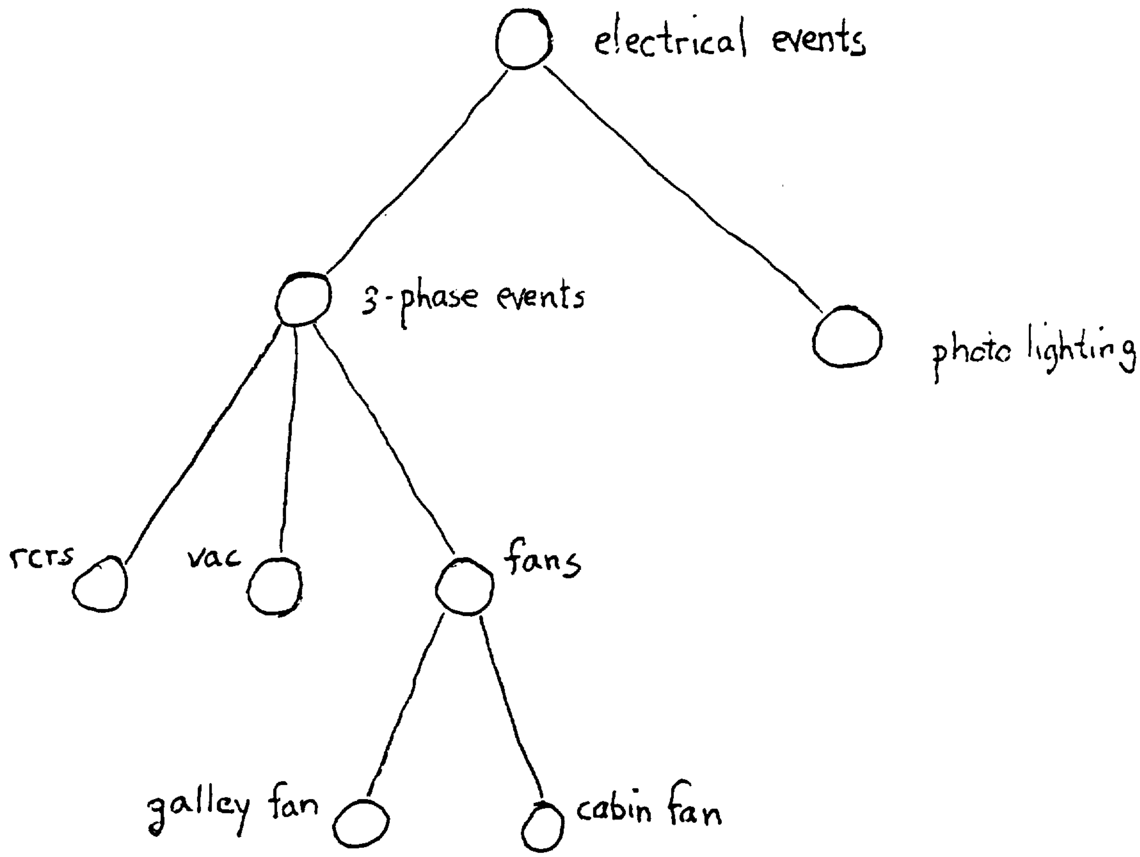
Our system is based on Fisher's COBWEB, a robust and accurate concept formation system.

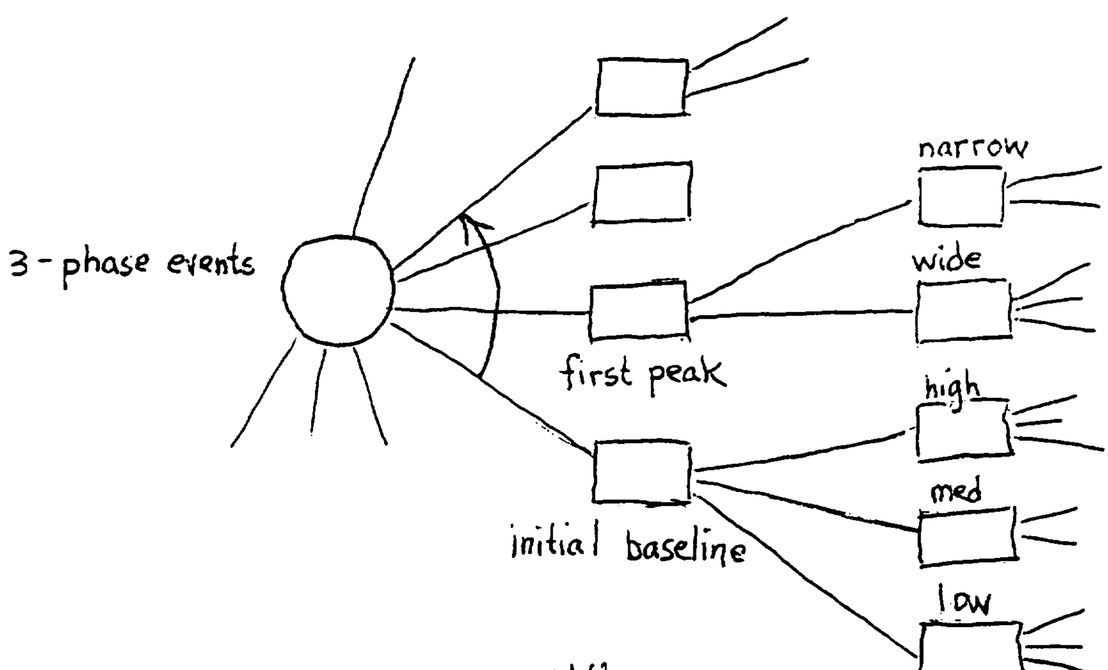
- probabilistic concepts organized hierarchically
- performance and learning mechanisms identical

• events represented as temporal structures

Given a new instance and a concept in the hierarchy:

1. Find the best match of the new instance to the concepts stored at the current level of the hierarchy
2. Compute the score for creating a new class containing only the new instance
3. Unless creating a new class, recursively classify the new instance in the hierarchy below the best class.


electrical events
3-phase events
photo lighting
rcrs
vac
fans
galley fan
cabin fan


3-phase events
first peak
initial baseline
narrow
wide
high
med
low

Preliminary Evaluation

Domain: thirty-six labeled electrical events from a three-phase power bus on the shuttle

- six different devices
- three amperage values at 0.1 sec. intervals over six secs.

Experimental design: cross-validation study testing a single instance at a time in two condtions:

- complete data: full six seconds of data
- partial data: events truncated to average of 0.975 seconds

Preliminary Results

	Complete Data	Partial Data	Most Frequent
Accuracy	91.7%	70.7%	22.2%

	cabfan	rcrs	galfan	vac	wcs	phot
cabfan	2			1		
rcrs		8				
galfan			7			
vac				6		
wcs					7	
phot		$0.6\bar{6}$	1		$0.3\bar{3}$	3

Future Work

- Include signature type information in training data
- Tuning for a given domain
- Efficiency of learning and classification
- Extend to handle abnormal events

Conclusions

A concept formation approach, such as developed in OXBOW, has several advantages and disadvantages:

- Pros
  - generality to a variety of temporal domains
  - scalable to a large number of concepts
  - may discover classes of abnormal events or interesting subclasses
- Cons
  - accuracy needs to be higher
  - implemented in Lisp and currently computationally unwieldy

Methodological Issues Raised

Preliminary exposure to this domain suggested several important issues relevant to future testing:

- quality of the training data
- quality of the testing data
- quality of the controllers

Results of the Santa Fe Time Series Competition

Andreas Weigend

Xerox PARC and
University of Colorado at Boulder

Most observational disciplines, including physics, biology and finance, try to infer properties of an unfamiliar system from the analysis of a measured time record of its behavior. There are mature techniques associated with traditional time series analysis. During the last decade, new approaches such as neural networks have emerged, promising results and insights not available with standard methods. However, the evaluation of this promise has been difficult. Adequate benchmarks were lacking, and most of the literature has been fragmentary and anecdotal.

Global computer networks enabled disjoint communities to attack these problems through the widespread exchange of data and information. In order to foster this process, we organized the "Time Series Prediction and Analysis Competition" under the auspices of the Santa Fe Institute during the fall of 1991. With the assistance of an advisory board from the relevant disciplines, we selected (and made generally available) a group of data sets that cover a broad range of interesting attributes.

* A clean physics laboratory experiment (NH_3 laser).
* Physiological data from a patient with sleep apnea.
* Tick-by-tick currency exchange rate data (Swiss Franc--US Dollar).
* A computer generated series designed for this competition.
* Astrophysical data from a variable white dwarf star.
* J S Bach's final (unfinished) fugue from "Die Kunst der Fuge."

The participants in the competition were asked to submit:

* Forecasts of the continuation of the data sets (that were withheld).
* Analyses of properties such as the number of degrees of freedom, the noise characteristics, and the nonlinearity of the system.
* Models of the governing equations.
* Descriptions of the algorithms employed.

In this talk, I will motivate our choice of the data sets, present some of the results of the competition, and close with some thoughts on the interplay between learning time series and characterizing dynamical systems.

(Joint work with Neil Gershenfeld, MIT)

The Future of Time Series: Learning and Understanding

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(This version: May 25, 1993)

Abstract. The use of a measured time series to characterize the nature of an observed system and to model its future behavior arises throughout scientific research. There are a number of new approaches to this very old problem that promise insights unavailable with traditional approaches, however in practice the application of techniques such as state-space reconstruction and neural networks has been hampered by results that can be unreliable and by the difficulty of relating their performance to that of mature algorithms. This article reports on a time series competition that was recently run through the Santa Fe Institute in order to bring together researchers from a range of relevant disciplines to help make meaningful comparisons between their approaches by analyzing common data sets. The design and results of the competition will be described, and the necessary theoretical and historical background to understand the successful entries will be reviewed.

THIS IS A DRAFT. THE FINAL VERSION IS TO APPEAR IN: *Predicting the Future and Understanding the Past: a Comparison of Approaches* (Proceedings of the NATO Advanced Research Workshop on Time Series Analysis and Forecasting, held in Santa Fe, New Mexico, May 14-17, 1992.) Edited by Andreas S. Weigend and Neil A. Gershenfeld (Reading, MA: Addison-Wesley, 1993).

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University of Colorado, Boulder, CO 80309-0430, USA.

Contents

THE SANTA FE TIME SERIES COMPETITION

Andreas S. Weigend

Neil A. Gershenfeld

- **Santa Fe Institute**
- **Stanford (ASW)**
- **Harvard (NAG)**
- **MIT Media Lab (NAG)**
- **Xerox PARC (ASW)**

Address after July 1993:
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Computer Science Department
University of Colorado at Boulder
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OVERVIEW

- Time Series
  - From linear to nonlinear paradigm
  - Understanding
    - From Yule to embedding
  - Learning
    - Emulate unknown structure
    - Generalization vs memorization
- SFI Results: Prediction
  - Filtered embedding (Sauer)
  - Neural network (Wan)
  - Hidden Markov model (Fraser)
- SFI Results: Characterization
  - Direct vs indirect (via prediction)
- The Future

INTRODUCTION

Three problems

- ❑ predict
  - short-term forecasts
- ❑ model
  - long-term behavior

    trajectory, attractor

    differential equations
- ❑ characterize
  - fundamental properties

    amount of noise

    degrees of freedom

Complementarity of *understanding* and *learning*

PARADIGM CHANGES

1. pre–1920's:

- global fit in time

2. 1920's to 1980's:

- linear modeling and prediction

  + superposition, easily understood
  – qualitative behavior limited
  – similar spectra from different systems

3. post–1980's:

- nonlinear paradigm

  computer simulation of nonlinear systems
  automatic data acquisition
  machine learning

SFI COMPETITION

- Set-up
  - August 1991: Data on server
  - January 1992: Deadline
- What happened?
  - more than 1000 people ftp'ed data
  - about 40 submitted predictions
- Follow-up
  - May 1992: NATO Workshop
  - July 1993: Book (A-W)
- Data remain available

  anonymous ftp to

  `ftp.santafe.edu`

UNDERSTANDING ↔ LEARNING

❑ Understanding

perspective: low dimensional DEQ's

– **Embedology vs Yule**

dimension of manifold

stochastic vs deterministic world view

Progess: recognize/characterize geometry

❑ Learning

perspective: search in function space

emulate unknown structure

strong vs weak models

Progress: learning ↔ understanding

❑ Generalization vs Memorization

perspective: large model spaces

good: more flexible

bad: problem of overfitting

Progess: model selection

PREDICTIONS

- **LASER DATA SET (A: 1,000 points)**

Smart **embedding:**

- ❑ **filtered delay coordinates**

  (Tim Sauer, George Mason U)

Smart **function approximation:**

- ❑ **connectionist network**

  (Eric Wan, Stanford U)

- **SYNTHETIC DATA (D: 100,000 points)**

Smart **estimation of prediction errors:**

- ❑ **hidden Markov model**

  (Andy Fraser, Portland State U)

NEURAL NETWORKS

Wan's architecture: 1-12-12-1

replaces ech connection by a delay line (25, 5, 5 lags)

1105 parameters: a puzzle?

neural networks:

limit **number of features**

but allow arbitrary nonlinearities

iterative method: implicit regularizer

early stopping / cross validation

vs"traditional" statistics:

limit **order of interactions**

HIDDEN MARKOV MODEL

Fraser and Dimitriadis

20-state model

local linear autoregressive filters of 8th order

4.5 transitions on average from each state

6,000 parameters

CHARACTERIZATION

Direct

- Redundancy:

  Incremental mutual information as function of embedding dimension

Indirect (via prediction)

characterize by analysis of performance

temporal structure in residual errors?

time reversal

surrogate data

- DVS modeling

- Connectionist

CHARACTERIZATION VIA PREDICTION

❑ Connectionist models

- **test error (out of sample error) as function of number of hidden units**

  use regularizer in training

- **effective dimension of hidden units**

  from eigenvalue spectrum of hidden units

❑ DVS models

- **test-error (out of sample error) as function of number of neighbors**

  construct family of local linear models
  with size of neighborhood as parameter
  (extremes: local look-up – global linear)
  plot out-of-sample error

`Deterministic vs Stochastic Plots'

REFERENCE

Predicting the Future and Understanding the Past:

A Comparison of Approaches

A.S.Weigend and N.A.Gershenfeld, eds

SFI Studies in the Sciences of Complexity

Addison-Wesley, Summer 1993.

Order number 62602 (pb), 62601 (hc)

(Addison-Wesley: **1-800-447-2226**)

Andreas Weigend

Xerox PARC and CU Boulder

weigend@cs.colorado.edu

The data sets as well as programs and analyses are available via anonymous ftp at

ftp.santafe.edu

Title: **Predicting the Future and Understanding the Past: a Comparison of Approaches**

Proceedings of the NATO Advanced Research Workshop on Time Series Analysis and Forecasting held in Santa Fe, New Mexico, May 14-17, 1992.

Editors: **Andreas S. Weigend and Neil A. Gershenfeld**

Series: **Santa Fe Institute Studies in the Sciences of Complexity**

Publisher: **Addison-Wesley, June 1993.**
Backorder: **Call A-W Order Department at 1-800-447-2226.**
Order numbers: 62601 (hardcover), 62602 (pbk).

Summary. This book presents a multi-disciplinary view of the state of the art in the areas of prediction and analysis of temporal sequences. Different methods to forecasting and characterization of time series are compared and contrasted in a comprehensive overview chapter by the editors. Details of these approaches, such as connectionist networks, surrogate data and filtered delay coordinates, are then explained by the individual researchers. All techniques are applied to a few carefully selected benchmark time series.

Why this book?

Most observational disciplines, including physics, biology and finance, try to infer properties of an unfamiliar system from the analysis of a measured time record of its behavior. There are mature techniques associated with traditional time series analysis. During the last decade, new approaches such as neural networks have emerged, promising insights not available with these standard methods. However, the evaluation of this promise has been difficult. Adequate benchmarks were lacking, and most of the literature has been fragmentary and anecdotal.

Global computer networks enabled these disjoint communities to attack these problems through the widespread exchange of data and information. In order to foster this process, the editors organized the *Time Series Prediction and Analysis Competition* under the auspices of the Santa Fe Institute during the fall of 1991. With the assistance of an advisory board from the relevant disciplines, they selected a group of data sets that cover a broad range of interesting attributes:

- Tick-by-tick currency exchange rate data (Swiss Franc – US Dollar).
- Physiological data from a patient with sleep apnea.
- Astrophysical data from a variable white dwarf star.
- A clean physics laboratory experiment (NH_3 laser).
- A computer generated series designed for this competition.
- J. S. Bach's last (unfinished) fugue from *Die Kunst der Fuge*.

The data was made generally available at **ftp.santafe.edu** (and will remain publicly accessible there). The participants in the competition were asked to submit:

- Forecasts of the continuation of the data sets (that were withheld).
- Analyses of properties such as the number of degrees of freedom, the noise characteristics, or the nonlinearity of the system.
- Models of the governing equations.
- Descriptions of the algorithms employed.

In order to explore the results of the contest, the editors organized a *NATO Advanced Research Workshop* in the spring of 1992. Workshop participants included members of the advisory board, representatives of the groups that had collected the data, participants in the contest, and some interested observers. Although the participants came from a broad range of disciplines, the discussions were framed by the analysis of common data sets and hence it was usually possible to find a meaningful common ground.

This volume now presents the results of both the competition and the workshop. One of its strengths is its focus on a common set of problems tackled by a variety of different methods.

Contents

The volume consists of three parts:

1. **Overview.** In the first part, the editors present the results of the competition and the workshop and analyze the advantages and disadvantages of the various techniques both in time series prediction and in characterization. In the area of prediction, recurring themes include the importance for careful assessments of the statistical reliability of the results, and the need to match the level of description of the model to the system being studied (from deterministic low-dimensional dynamics to stochastic processes).
   In the area of characterization, several techniques are presented that try to estimate the number of degrees of freedom of the system or the rate at which the system loses memory of its state. A common feature here is the desire to reduce the sensitivity to geometrical artifacts abundant in standard methods (such as correlation dimensions and Lyapunov exponents). The methods discussed include information-based measures as well as estimators based on evaluating the reliability of the embedding.
2. **Details.** In the central part, fifteen scientists who applied their methods to the data, motivate and describe their ideas in individual chapters. Although from a wide variety of different disciplines (statistics, experimental and computational physics, electrical and mechanical engineering, economics and finance, biology and medicine, musicology and others), all contributors focus on the same sets of data. Their strictly refereed contributions are as self-contained as possible.
3. **Data.** In the third part, the scientists who contributed the time series describe the scientific questions behind their data and the kinds of models typical in their home disciplines. They then analyze their data with the current methods in their respective fields, and finally gauge what they have learned from the new techniques that were applied to their data in the competition and at the workshop.

The book also explores the relationship between time series methods and the analysis of spatio-temporal problems (there appear to be natural connections, such as the use of spatial analogs of time-delay embedding). It closes with some thoughts pointing towards the future of prediction by the scientific advisors to the project.

Outlook

This volume is a valuable timely contribution to the rapidly growing field of nonlinear time series analysis. It contains the results of the most rigorous comparison of different methods to time series prediction–if not to machine learning in general–to date. This breadth and competence was achieved through the high-profile *Time Series Prediction and Analysis Competition* at the Santa Fe Institute and the subsequent *NATO Advanced Research Workshop* that brought together an international group of time series experts from a wide variety of fields. This volume will serve as a unique multi-disciplinary reference of the present state of analyzing and forecasting time series.

Editors

Andreas Weigend received his PhD from Stanford University and was a postdoc at Xerox PARC (Palo Alto Research Center). He is Assistant Professor in the Computer Science Department and Institute of Cognitive Science at the University of Colorado at Boulder.

Neil Gershenfeld received his PhD from Cornell University and was a Junior Fellow at Harvard University. He is Assistant Professor in the Physics Department and Media Lab at MIT.

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Shallow and Deep Knowledge Techniques for Diagnosis of Time-dependent Data

Steve A. Chien, Nicolas F. Rouquette,
Leonard K. Charest, Jr., and E. Jay Wyatt

Jet Propulsion Laboratory
California Institute of Technology

Increasing complexity of complex process control applications have posed difficult problems in fault detection, isolation, and recovery (FDIR). Shallow and deep knowledge-based diagnosis techniques from Artificial Intelligence offer some promise in addressing the problems. Shallow knowledge techniques rely on large amounts of data/examples to characterize the behavior space. In contrast, deep models require well-understood behavioral models of the components in the target system. In order to support Space Station Freedom (SSF) design and testbed activities, we have developed shallow and deep-level diagnosis models for SSF systems from the Environmental Control and Life Support System (ECLSS) and the External Active Thermal Control System (EATCS).

In the shallow knowledge diagnosis system, classified examples of faults are used as training data for a decision tree induction system. In order to deal with the complexity that faults can occur at various times within the sensor polling cycle, the input data is processed to contain examples of all possible fault/sensor poll sychronizations.

The deep knowledge diagnosis technique is an extension of classical model-based diagnosis techniques to deal with sparse data, noise, and complex non-invertable numerical models. In this approach, a two phased approach to diagnosis is used. In the first phase, an extension of constraint suspension is used to generate a set of candidate component faults. In the second phase, a generalized simulation is used to determine which of the remaining candidate faults best matches the observed data. Because the steps are ordered in terms of d=ecreasing robustness, in the event of a novel, unforseen fault, operators can fall back upon candidate sets from earlier phases of diagnosis.

Shallow and Deep Knowledge Techniques for Diagnosis of Time-dependent Data

Steve Chien, Nicolas Rouquette,
Richard Doyle, Leonard Charest, and E. Jay Wyatt

Jet Propulsion Laboratory
California Institute of Technology

Shallow diagnosis techiques

- ☐ - rely upon datasets including examples of faults
- ☐ and nominal behavior

- ☐ - learn rules using decison-tree generation techniques
- ☐ to discriminate between observed classes

Outline

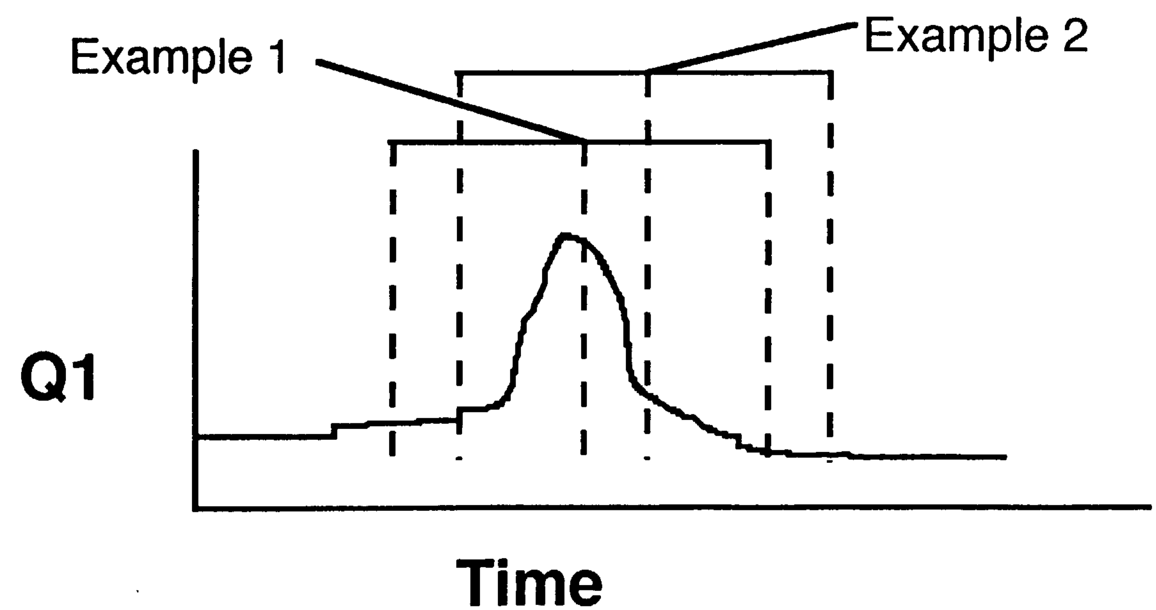
Shallow Methods

sensor placement for SSF ECLSS

Deep Methods

model-based diagnosis to support SSF EATCS testbed

Time-series Polled Data

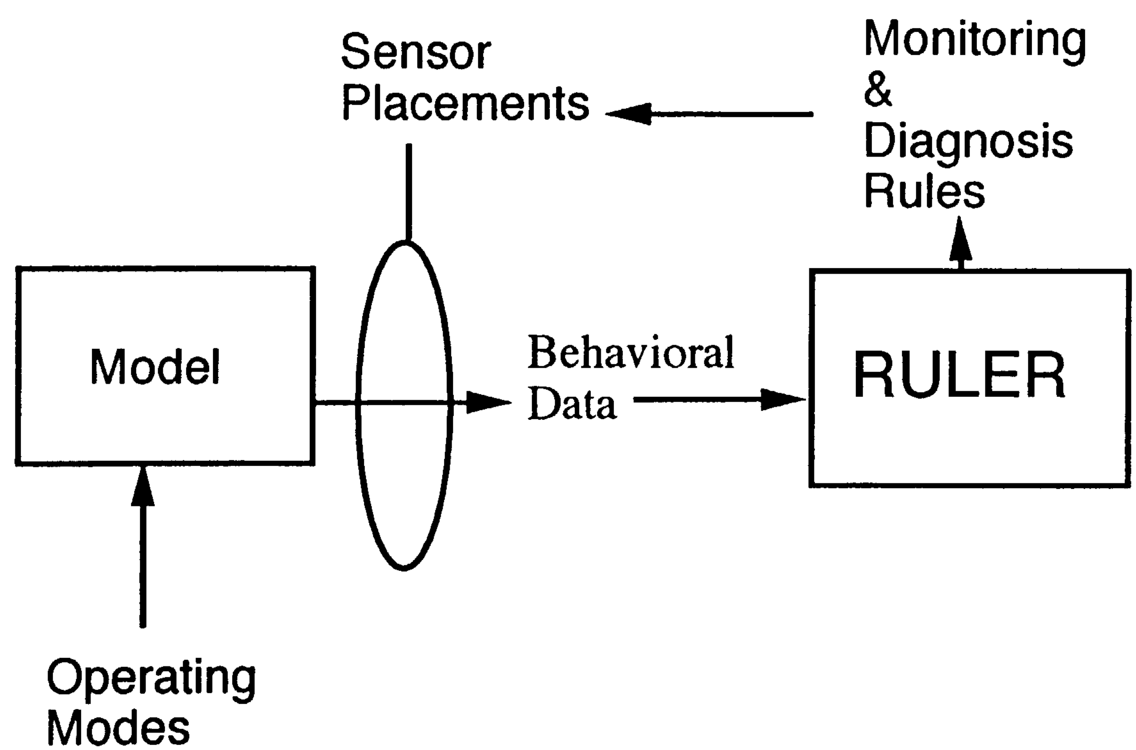


Goal of Shallow Diagnosis Work

- Support sensor placement analysis

☐ - rules can be used to assess adequacy
☐ of current sensor suite

☐ - analysis of attributes can be used to
☐ conjecture sensros to assist in diagnosis


Sensor
Placements
Monitoring
&
Diagnosis
Rules
Model
Behavioral
Data
RULER
Operating
Modes

Shallow Diagnosis v. Signature Recognition

- used ML techniques to learn shallow diagnosis rules to assist in sensor placement

- sensor placement problem is of attribute selection rather than feature selection

- almost no model of temporal relatedness of attributes

TESTBED

- Potable Water Processor (PWP) ,
  Vapor Compression and Distillation (VCD)
  subsystems of Space Station Life Support

- PWP:
  ~ 50 components
  ~800 quantities
  ~ 50 fault classes
  ~100 fault instances (incl. sensor faults)

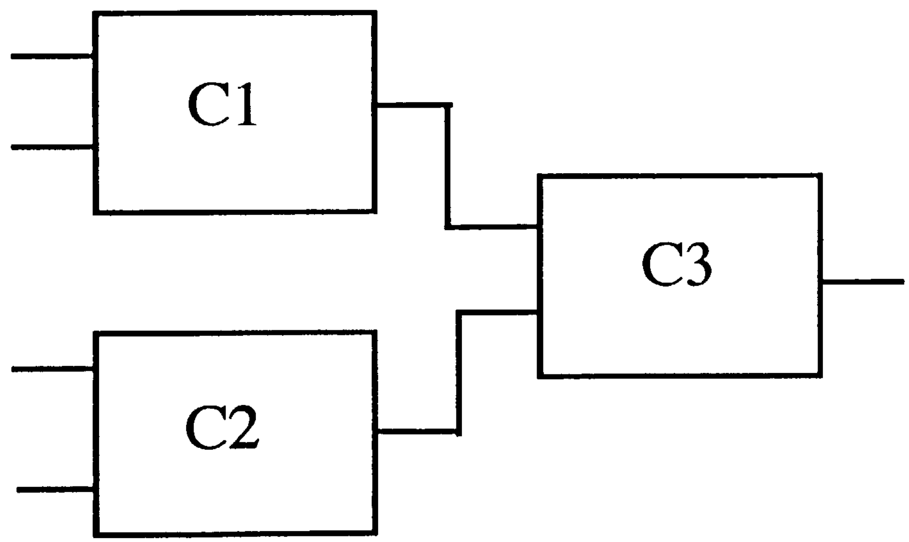
Deep Knowledge Diagnosis Methods

Model-based diagnosis to support the External Active Thermal Control System (EATCS) at JSC

In collaboration with Tim Hill and Charlie Robertson of McDonnell Douglas

Investigating extensions of constraint suspension to perform diagnosis

Constraint Suspension



each component C has a set of constraints K relating its inputs and outputs

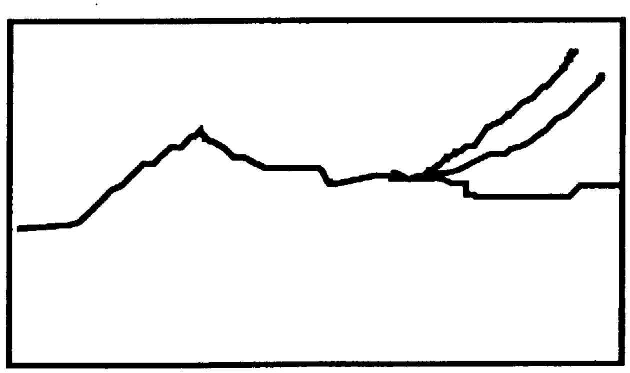
for each constraint, suspend it, if the remaining model is consistent with observations, suspect C

Constraint Suspension v. Signature Recognition

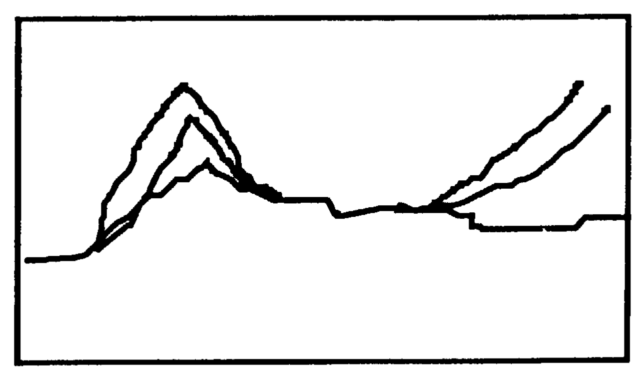
Each constraint is consistent with a class of signatures

The set of signatures consistent with a set of constraints is the intersection of those consistent with the individual constraints

Constraint suspension suspects components with constraints which force inconsistency of the observed signature



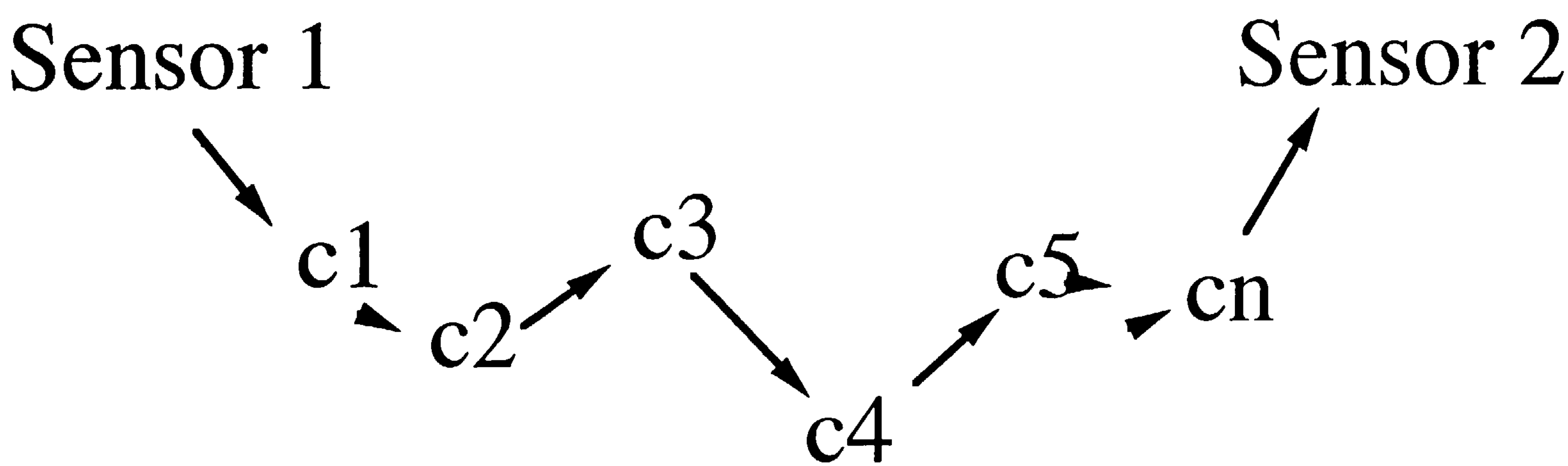
signatures consistent with K



signatures consistent with relaxed K

Constraint Equivalence

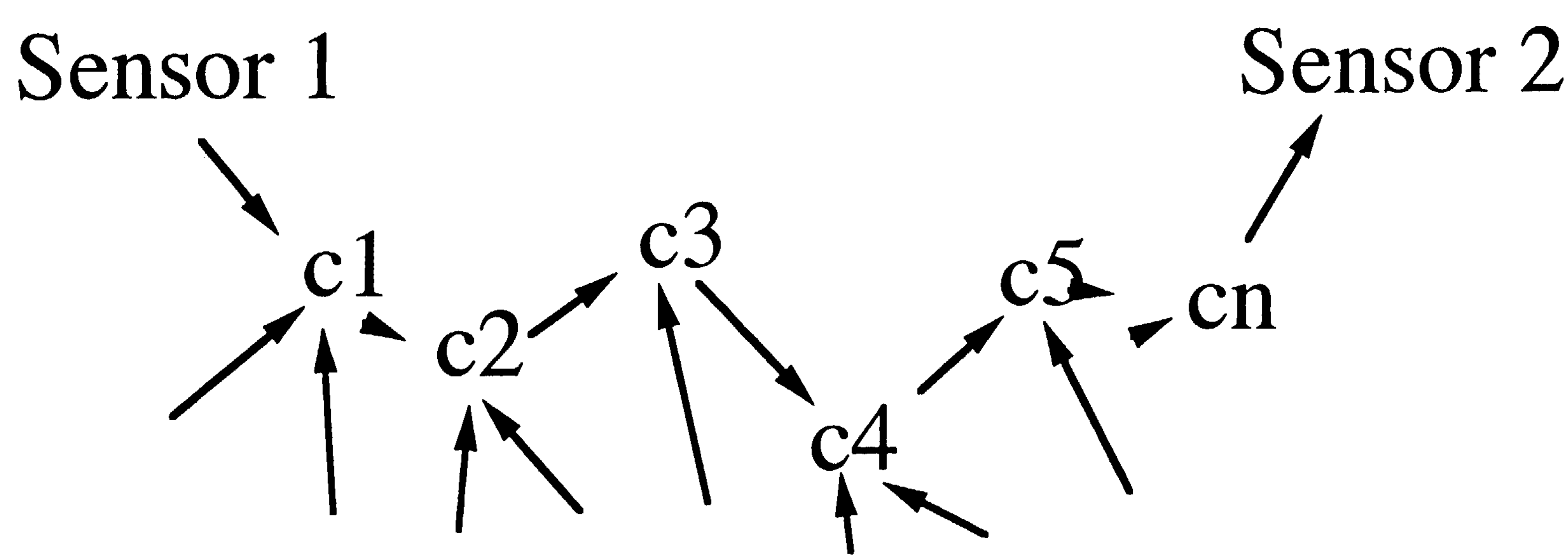
Undersensing causes many constraints to be equivalent in constraint suspension



analysis of causal graph -> constraint sets

Fan-in of unsensed quantities

Default value assumptions needed to strengthen model



Non-invertable constraints

$$
\begin{array}{l}
A \searrow \\
B \rightarrow C1 \longrightarrow D \\
C \nearrow
\end{array}
$$

can only check consistency
if have A, B, C

Multi-Stage Diagnosis

constraint suspension alone too weak

currently investigating further matching techniques based upon fault models

-qualitative fault models

-forward simulations

MBD Application Domain

EATCS Thermal Control for SSF

mechanisms modelled more complex than ECLSS

multiple solution strategies

Shallow v. Deep Diagnosis

simple discriminations	complex models?
novel classes ?	adaptation of techniques & rep

Summary

AI/diagnosis focused on attribute selection

many areas for synergy:

temporal fuzzy matching for MBD

Neural Networks for Prediction

Claudia Meyer,
NASA Lewis

Sensors fail at a much higher rate than any other component on the SSME. Failures of redlined sensors have been responsible for premature engine cutoffs during ground test firings and flight. Also, as advanced safety algorithms are developed and tested, validation of a large number of performance sensors has become necessary. Sensor validation is also a vital component of an automated post-test diagnostic system since failed sensors must be identified before engine health assessments can be made.

Toward this end, NASA LeRC has been leading efforts in the SSME sensor validation area. We have focussed on analytical redundancy, a technique in which a sensor's value is predicted by using other sensor values and known relations among the sensor values. The sensors and the set of relations among them define a network. A methodology for fusing or combining the evidence from the sensors and relations in a network has been developed under contract using Bayesian probability theory.

The greatest challenge in building these networks has been the development of analytical redundancy relationships which are valid over a large number of engines on all three test stands at Stennis. Three analytical redundancy approaches have been considered: characteristic equations, empirical correlations and neural networks. The characteristic equations and empirical correlations are being developed under contract, while the neural network activity has been in-house. Neural networks are well-suited for approximating complex nonlinear systems and can uniformly approximate any continuous function. Feedforward neural networks with one and two hidden layers have been used to predict various critical parameters during both the startup transient and mainstage operation of the engine. Time windows of data from related parameters have been used as network inputs. These networks were trained on data from nominal firings of one engine and validated using data from other nominal firings of the same engine. Good prediction accuracy was achieved. The behavior of the mainstage networks in the event of a hard input sensor failure has been characterized. Good prediction accuracy can be maintained when a synthesized value of the failed input is substituted for the faulty sensor.

One of the problems associated with mainstage training is the large amount of test data that is available for each test firing (more than 12000 patterns for a typical 500 sec duration test firing). Methods for reducing the number of patterns are currently being investigated. One approach involves the use of learning vector quantization for data compression. The other approach involves orthogonal least squares methods which are often used in conjunction with radial basis function networks.

Another interesting aspect of this project has been the use of genetic algorithms to select the inputs to a neural network function approximator. This input selection technique has been of particular interest since it could suggest sensor placement on future engines for analytical redundancy of critical parameters, in addition to generating an optimal or near-optimal set of inputs for a critical parameter within an existing sensor suite.

Neural Networks for SSME Function Approximation

NASA Workshop on Automation of Time Series, Signatures and Trend Analysis

May 12, 1993

by

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OBJECTIVE

TO DEVELOP MODELS THAT CAN BE USED FOR REAL-TIME SAFETY AND POST-TEST DIAGNOSTICS

- SENSOR FAULT DETECTION AND ISOLATION / SIGNAL RECONSTRUCTION
- ENGINE FAULT DETECTION AND DIAGNOSIS

SSME PERSPECTIVE

- OVER 1500 HOTFIRE TESTS
- CHANGING TEST OBJECTIVES
- VARIATIONS ACROSS TEST STANDS AND ENGINES
- LIMITED NUMBER OF FAILURES / CHANGING FAILURE MODES
- EVOLVING ENGINE HARDWARE
- SPARSE INSTRUMENTATION
- DIFFERENT SOURCES OF SENSOR DATA

MOTIVATION FOR SSME SENSOR VALIDATION

- SENSORS FAIL AT A MUCH HIGHER RATE THAN ANY OTHER ENGINE COMPONENT
- FAILURES OF REDLINED SENSORS HAVE RESULTED IN PREMATURE ENGINE CUTOFFS DURING GROUND TEST FIRINGS AND FLIGHT (STS-51F)
- SENSOR VALIDATION IS REQUIRED TO PREVENT FALSE ALARMS FROM ADVANCED SAFETY ALGORITHMS
- AUTOMATED POST-TEST DIAGNOSTIC EVALUATIONS REQUIRE DATA VALIDATION

ANALYTICAL REDUNDANCY

THE USE OF INFORMATION FROM DISSIMILAR SENSORS TO PROVIDE AN ESTIMATE OF A MEASURED PARAMETER

- TYPICALLY USED TO DETECT SOFT FAILURES
- PROVIDES REDUNDANT SIGNAL FOR SENSOR VALIDATION WITHOUT REQUIRING HARDWARE REDUNDANCY
- ENGINE DIAGNOSTIC SYSTEM OR SAFETY SYSTEM CAN CONTINUE TO REASON USING A RECONSTRUCTED SIGNAL IN THE EVENT OF A SENSOR FAILURE
- MAY BE REQUIRED FOR CONTROL OF SPACE ENGINE (ENGINE IS LRU)

ANALYTICAL REDUNDANCY TECHNIQUES

- EMPIRICAL BINARY RELATIONS: LINEAR AND NONLINEAR REGRESSION EQUATIONS

    USE MOST HIGHLY CORRELATED PARAMETERS WHICH ARE PHYSICALLY REASONABLE

- ENGINE CHARACTERISTICS

PUMP AFFINITY	$\Delta P/N^2$=CONSTANT
LINE RESISTANCE	$\Delta P/Q^2$=CONSTANT

- NEURAL NETWORKS: WELL SUITED FOR MODELING COMPLEX NONLINEAR RELATIONSHIPS BETWEEN OBSERVED SYSTEM VARIABLES

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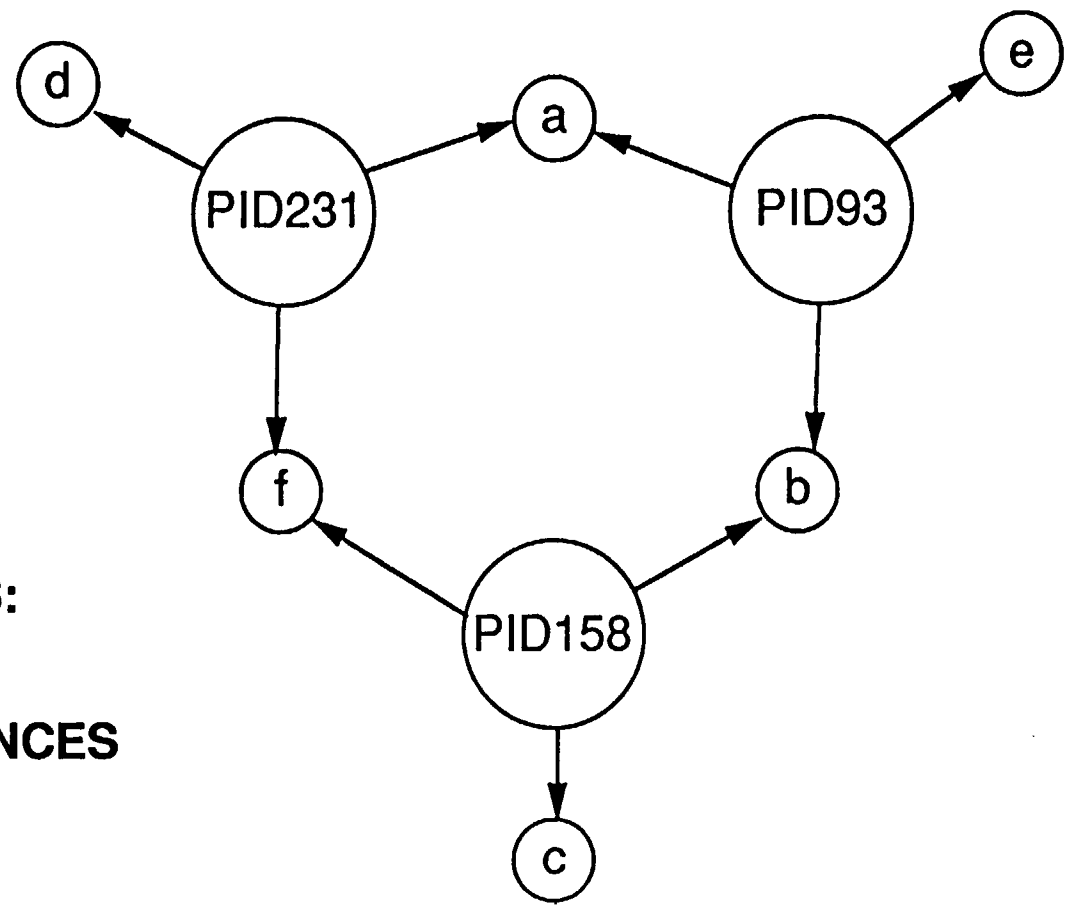
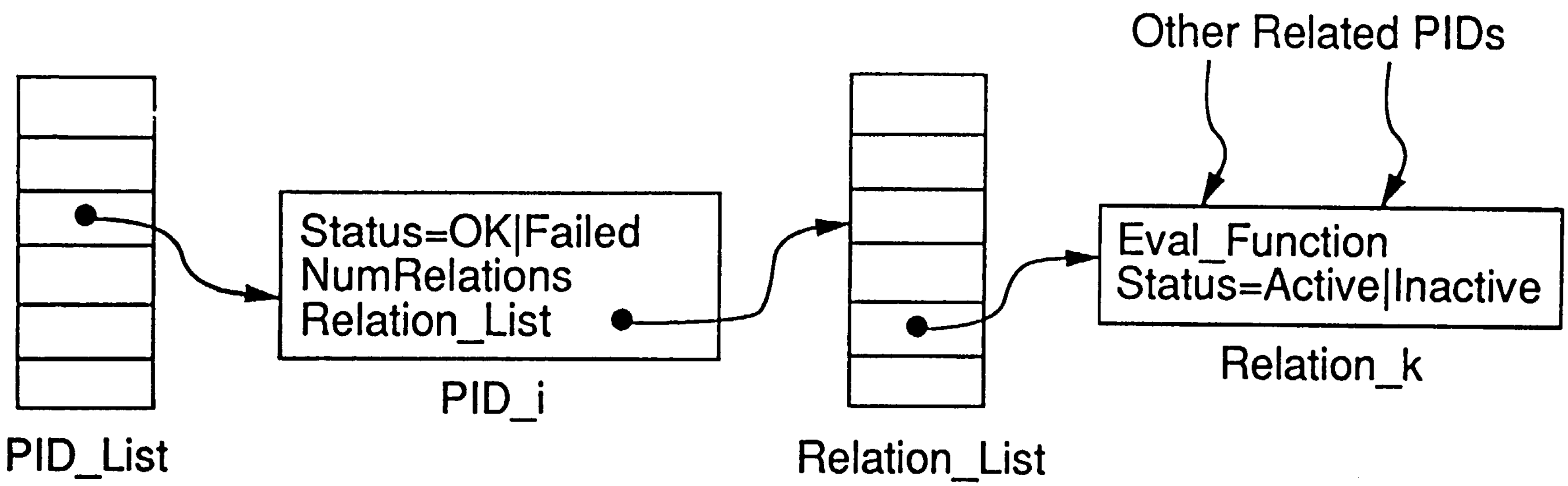
INFORMATION FUSION THROUGH BAYESIAN BELIEF NETWORKS



- EACH NODE IS A RANDOM VARIABLE
- NODES HAVE TWO STATES: OK AND FAILED
- ARCS REPRESENT INFLUENCES

SOFTWARE DESIGN AND DATA STRUCTURES



BASIC ALGORITHM:

FOR EVERY PID EVALUATE ACTIVE RELATIONS IN RELATION_LIST
ONLY UNTIL PID IS VALIDATED

WHY NEURAL NETWORKS?

- EXACT MATHEMATICAL RELATIONSHIPS BETWEEN OBSERVED SYSTEM VARIABLES ARE USUALLY UNKNOWN
- NEURAL NETWORKS CAN UNIFORMLY APPROXIMATE ANY CONTINUOUS FUNCTION
- HIGHLY PARALLEL ARCHITECTURE OF NEURAL NETWORKS FACILITATES REAL-TIME IMPLEMENTATION

APPLICATION ISSUES

- SELECTION OF MODEL INPUTS
- SELECTION OF WINDOW SIZE
- CREATION OF DATA SETS FOR TRAINING
  - TEST FIRINGS
  - DATA POINTS
- SELECTION OF HIDDEN LAYER ARCHITECTURE
- NOMINAL ENGINE PHENOMENA

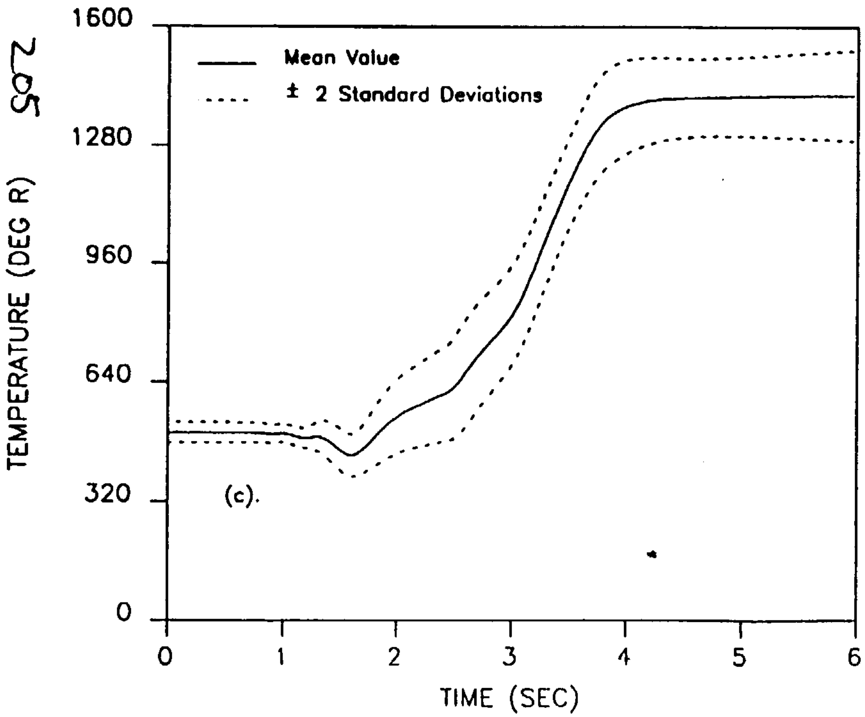
APPROACH

- MODELS WERE DEVELOPED FOR CRITICAL PARAMETERS DURING STARTUP AND MAINSTAGE
- NETWORKS WERE TRAINED ON DATA FROM TWO NOMINAL TEST FIRINGS USING BACKPROPAGATION
- THE TRAINED MODELS WERE TESTED WITH DATA FROM ADDITIONAL NOMINAL FIRINGS

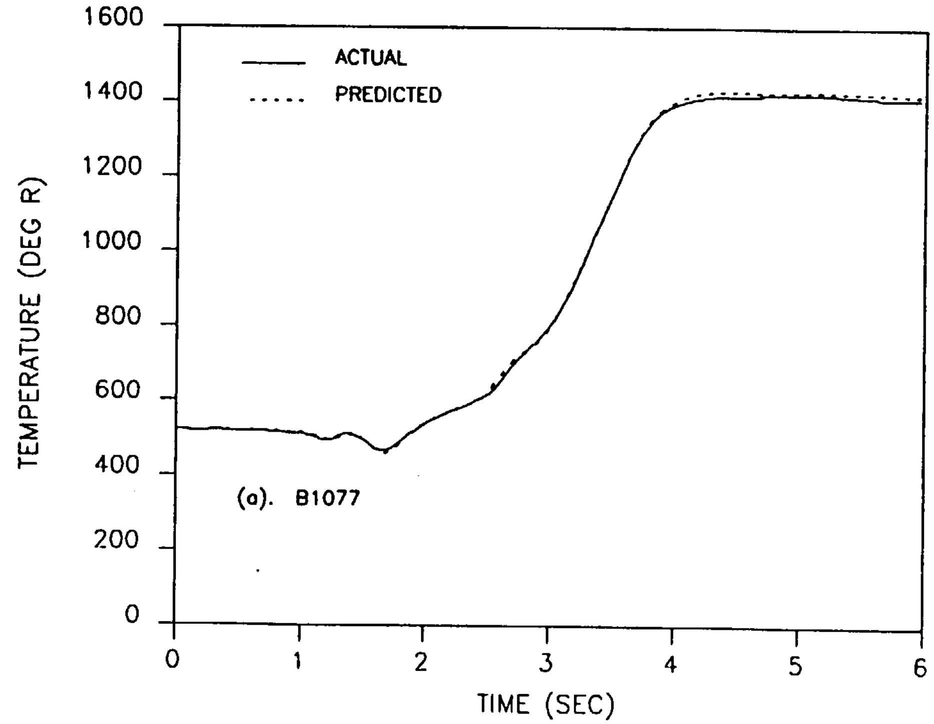
STARTUP RESULTS

HPOT DISCHARGE TEMPERATURE

NOMINAL 2-SIGMA VARIATION DURING STARTUP



ACTUAL AND NEURAL NETWORK PREDICTED SIGNALS



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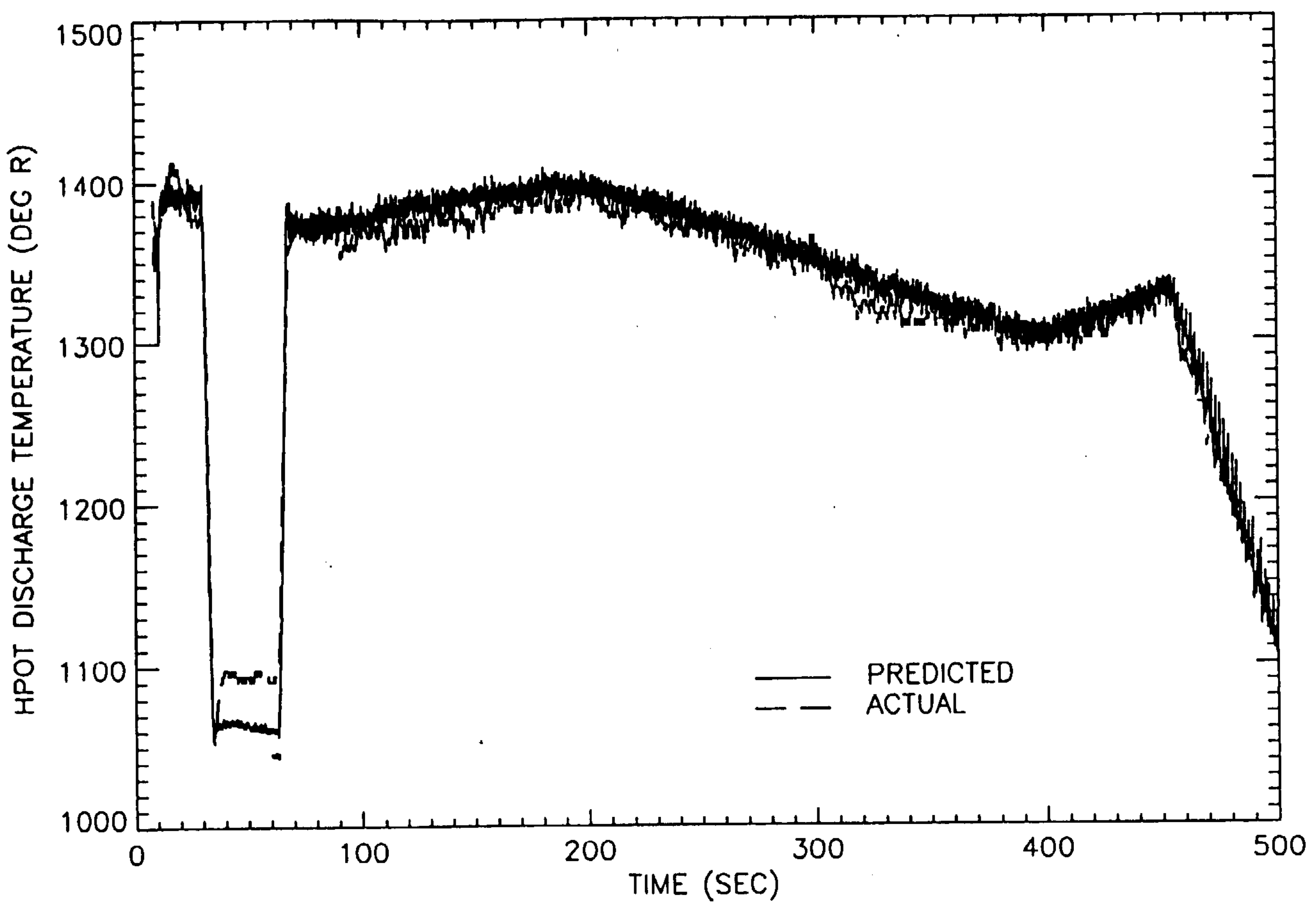
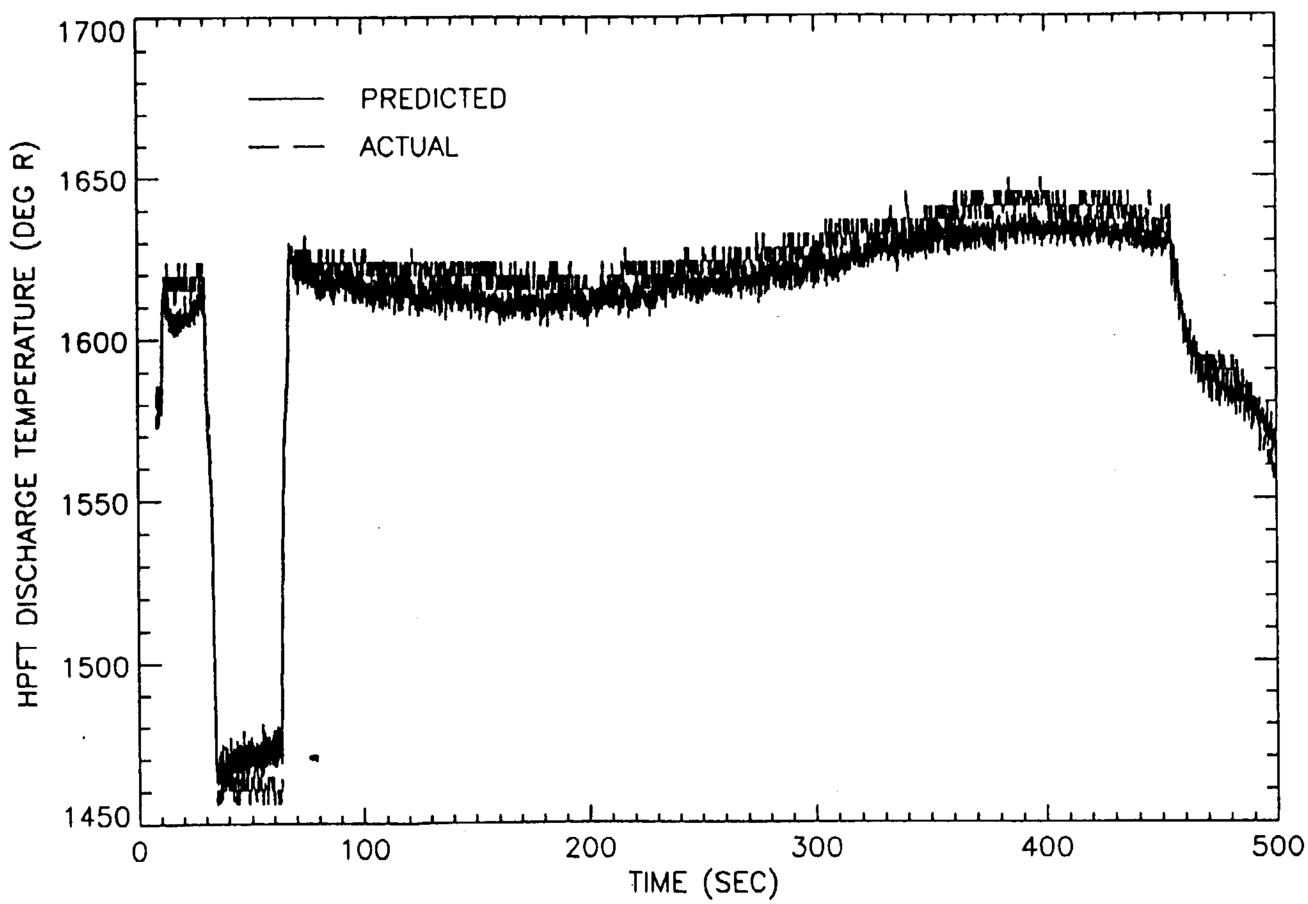
HPOT DISCHARGE TEMPERATURE

MODEL PERFORMANCE ON VALIDATION TEST FIRING



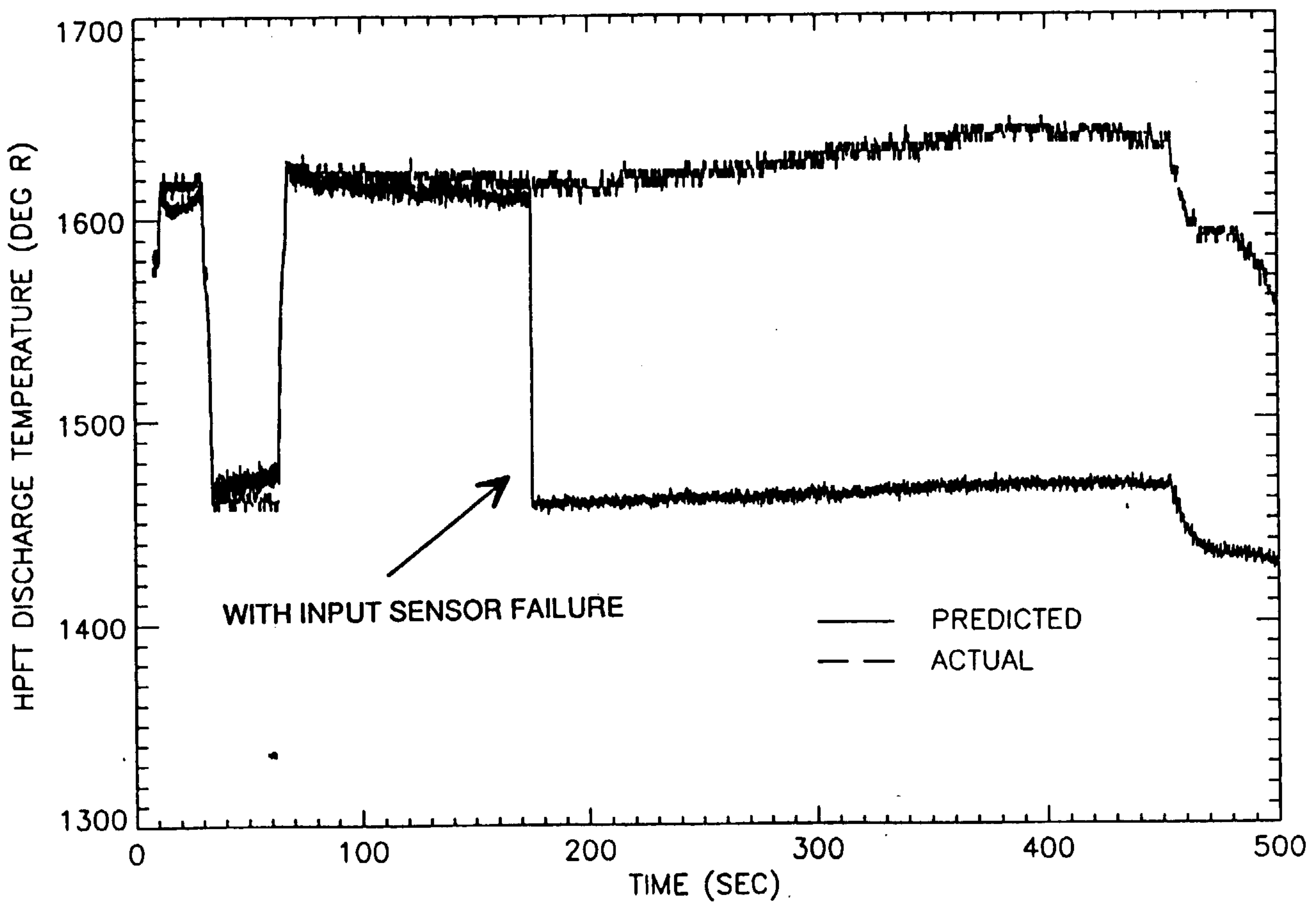
HPFT DISCHARGE TEMPERATURE

MODEL PERFORMANCE ON VALIDATION TEST FIRING



HPFT DISCHARGE TEMPERATURE

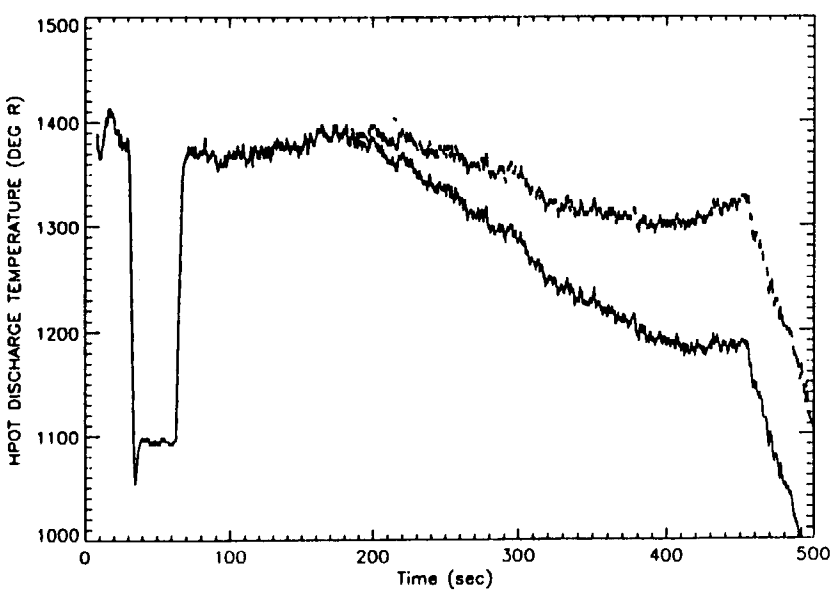
MODEL PERFORMANCE WITH INPUT SENSOR FAILURE



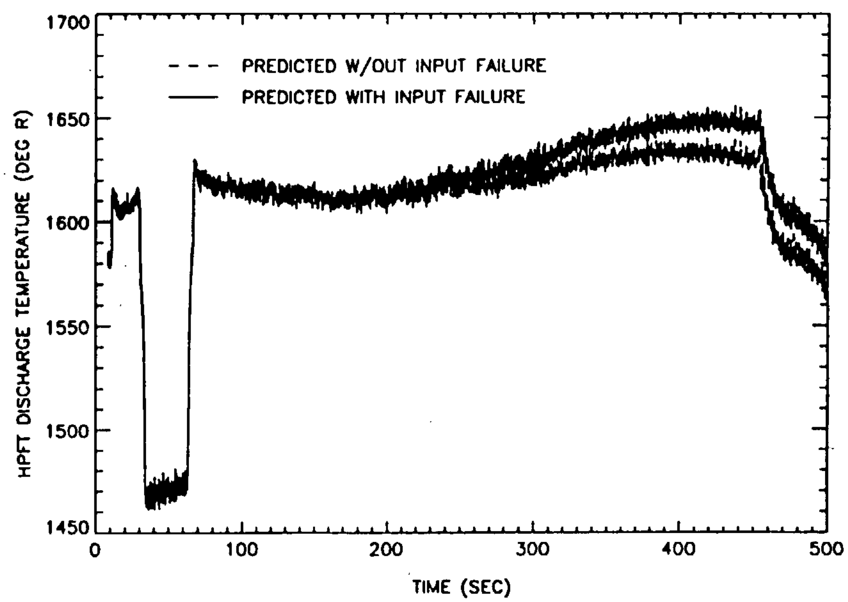
HPFT DISCHARGE TEMPERATURE

MODEL PERFORMANCE WITH INPUT SENSOR FAILURE

DRIFTING INPUT

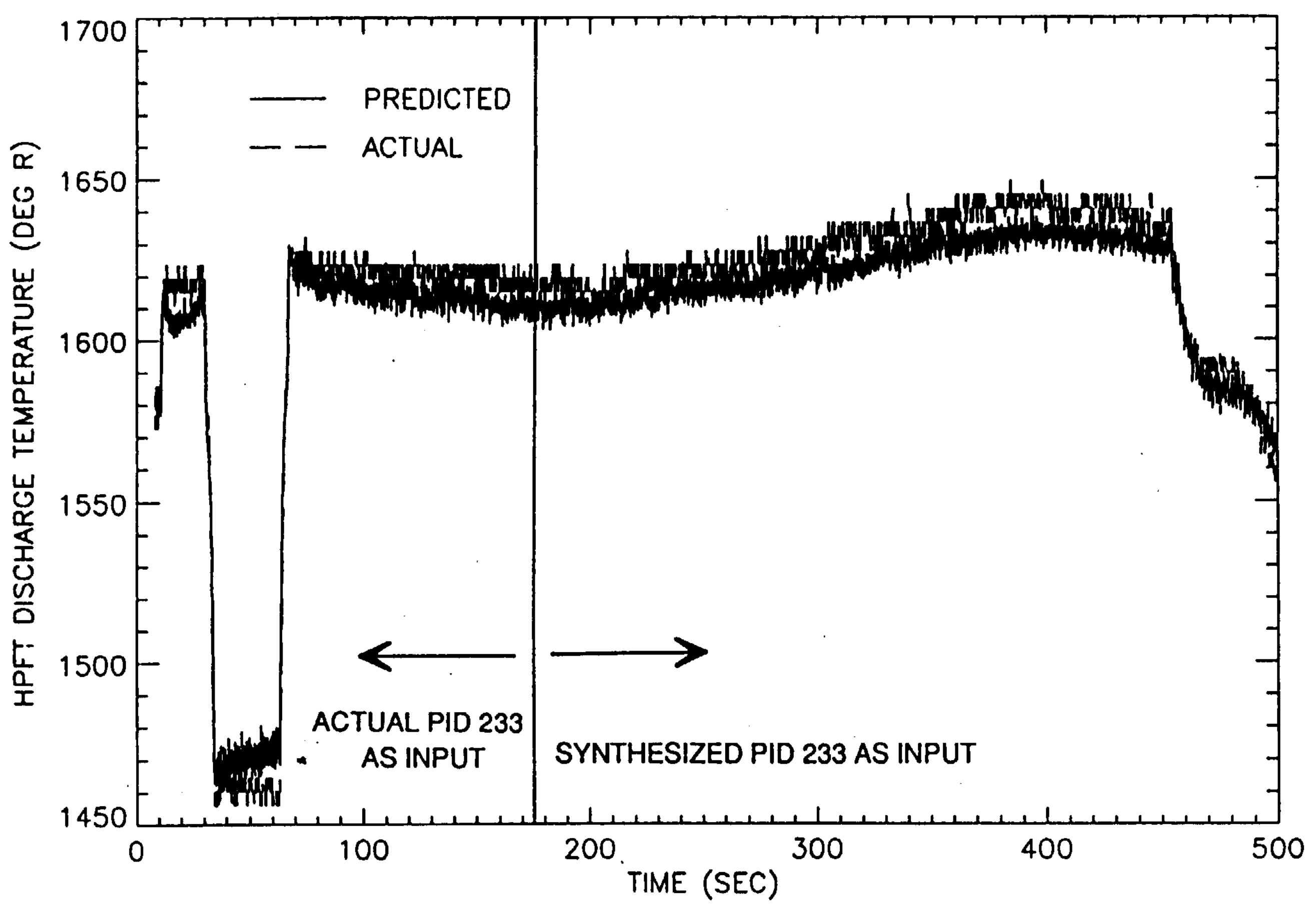


PREDICTION WITH FAILED INPUT



HPFT DISCHARGE TEMPERATURE

MODEL PERFORMANCE WITH SYNTHESIZED INPUT



REMARKS

- NEURAL NETWORKS CAN BE USED TO MODEL CRITICAL PARAMETERS THROUGHOUT THE THRUST PROFILE

- ENGINE TO ENGINE AND TEST STAND TO TEST STAND VARIATIONS CONTINUE TO BE A PROBLEM

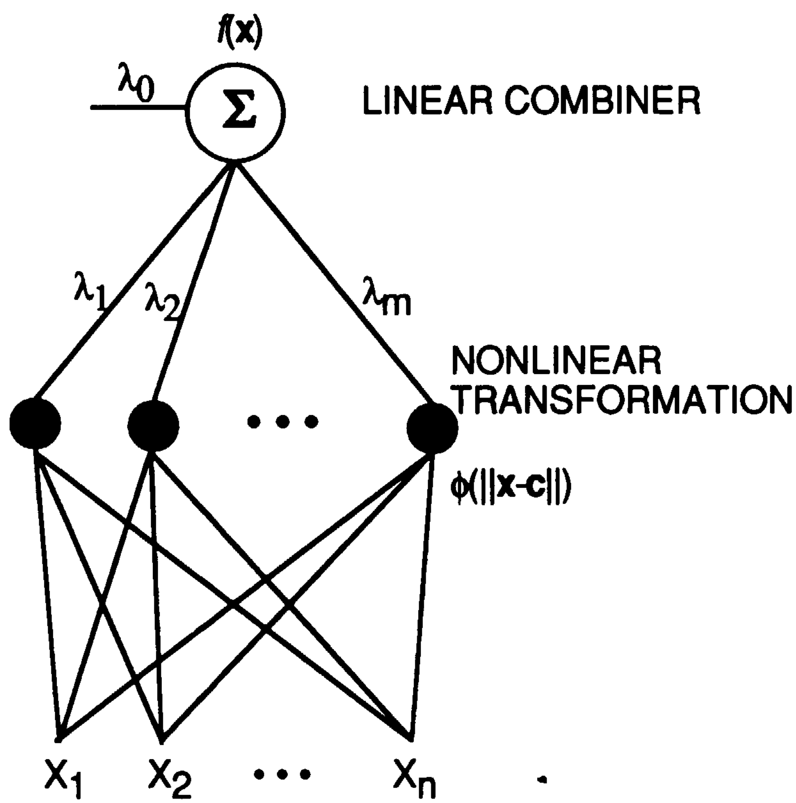
    - CAN MODEL BE BIASED TO CURRENT TEST FIRING?
    - EFFICIENT UPDATING OF MODELS AS NEW TEST DATA BECOMES AVAILABLE

- A METHODOLOGY FOR THE SYSTEMATIC SELECTION OF TRAINING DATA IS DESIRED

    - WHAT IS AN APPROPRIATE TRAINING SET?
    - SAFETY ALGORITHM WORK INDICATES THAT TEST FIRINGS CAN BE CLUSTERED

- RECURRENT NETWORKS

RBF NETWORKS FOR FUNCTION APPROXIMATION



- STRAIGHTFORWARD ARCHITECTURE
- CLUSTER CENTERS OBTAINED SYSTEMATICALLY
  - K-MEANS CLUSTERING
  - KOHONEN'S LVQ
  - OLS
- FAST TRAINING ($\lambda_1, \lambda_2, \ldots, \lambda_m$)

MAINSTAGE DATA COMPRESSION USING LVQ

- COMPUTATIONALLY INTENSIVE
- DOES NOT REQUIRE SETTING A LARGE NUMBER OF TOLERANCES

ACTUAL SIGNAL

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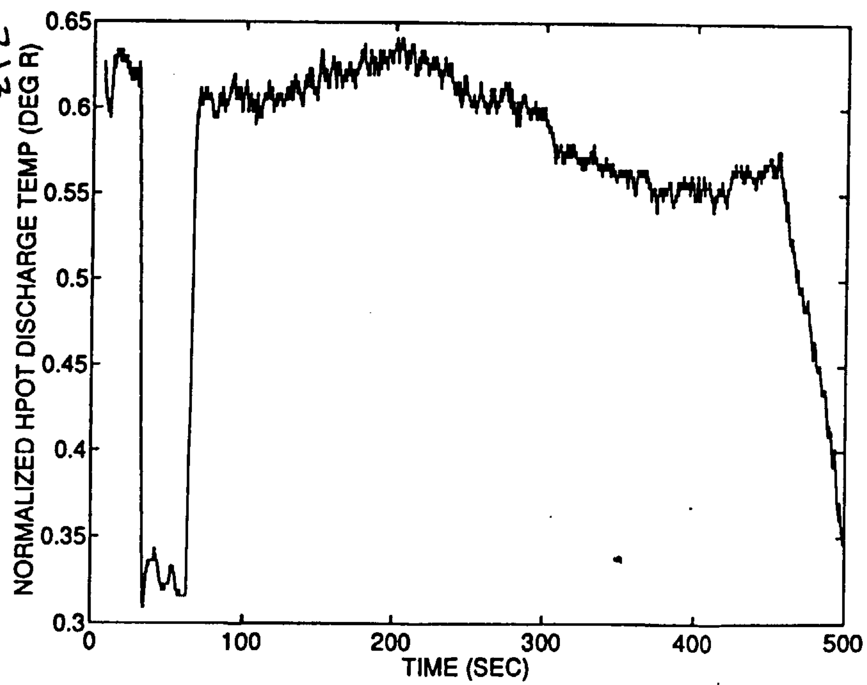
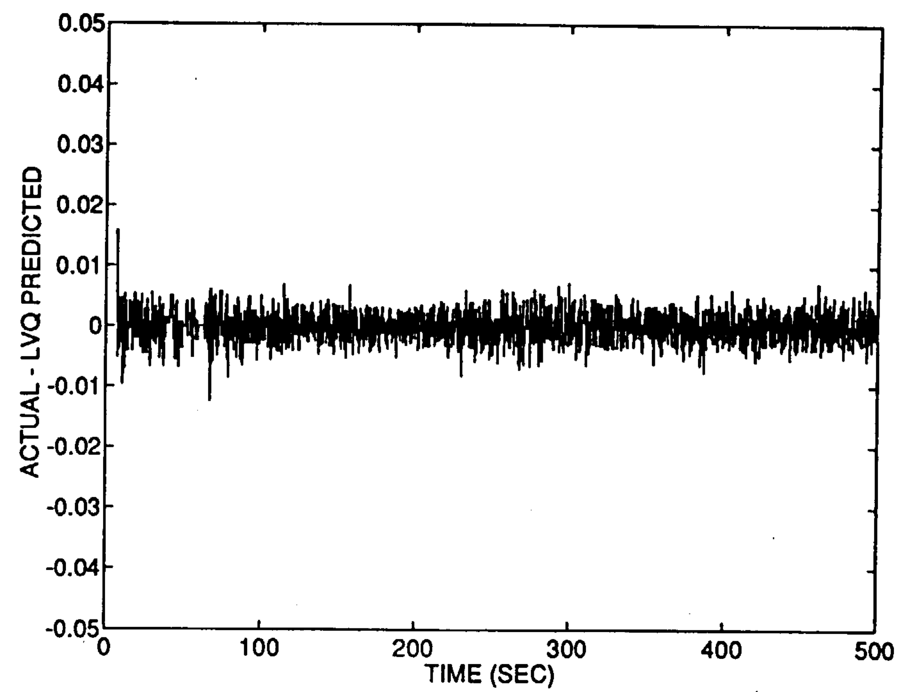


10:1 COMPRESSION ERROR

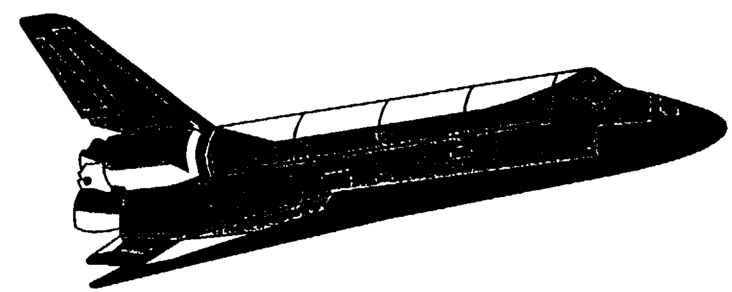


System Trend Analysis Reduction Tool

W. Joseph Elliott,
Analex Systems and KSC

A computer program was written using Statistical Process Control (SPC) methodology in order to prioritize Ground Support Equiment (GSE) systems for further problem investigation. Problem data from approximately 2500 GSE systems were retrieved from the Problem Reporting and Corrective Action (PRACA) database at KSC. Following Program processing, thirty-one systems failed one or more defined evaluation criteria. These systems then becamse prime candidates for detailed investigation of problem occurrences. Initial application of the program focused on critical GSE systems. The program has since been modified to address non-critical GSE and Shuttle flight systems.

SYSTEM TREND ANALYSIS REDUCTION TOOL



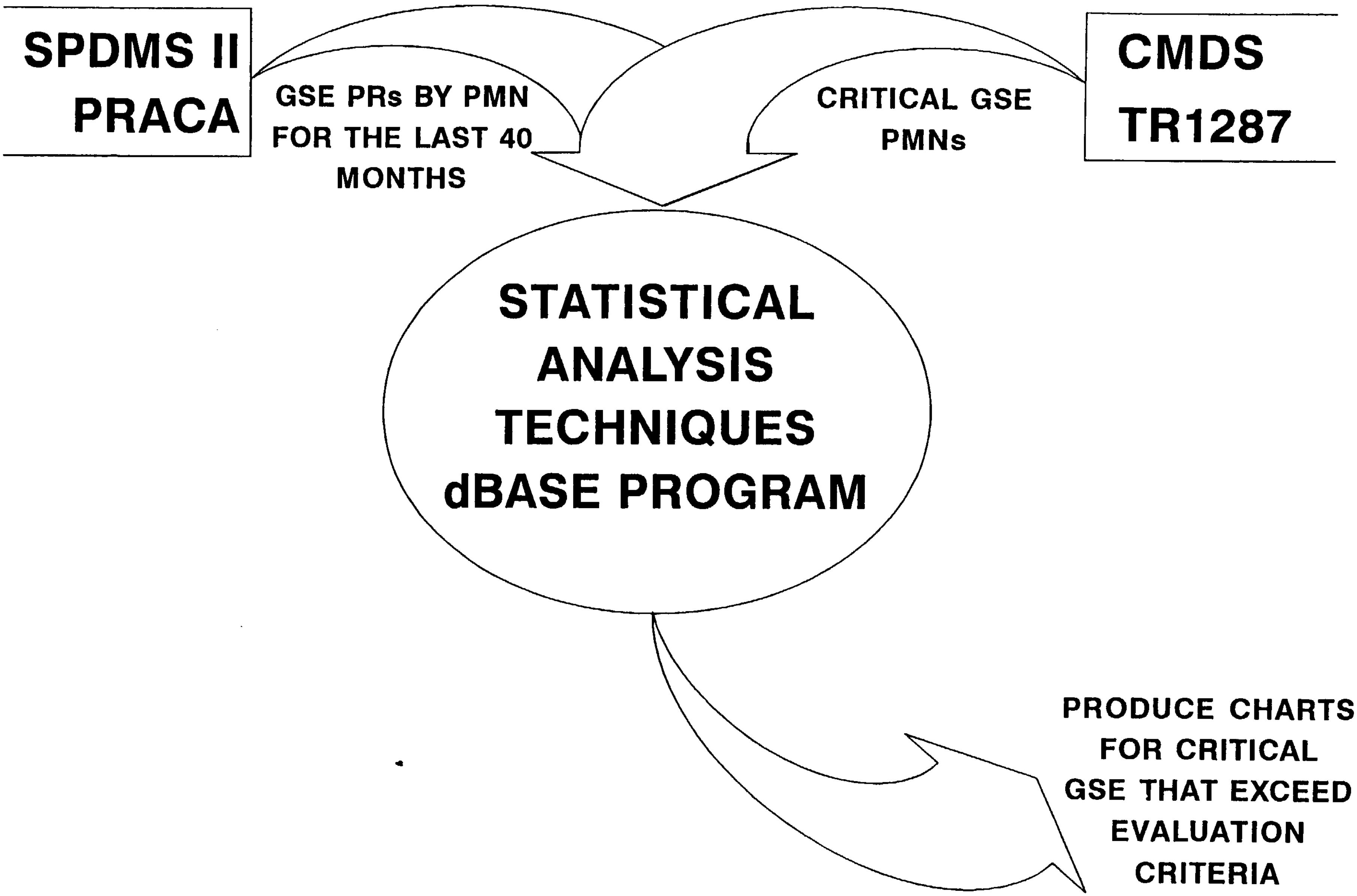
SYSTEM TREND ANALYSIS REDUCTION TOOL

PURPOSE:
TO DETERMINE AND PRIORITIZE SYSTEMS FOR PROBLEM INVESTIGATIONS

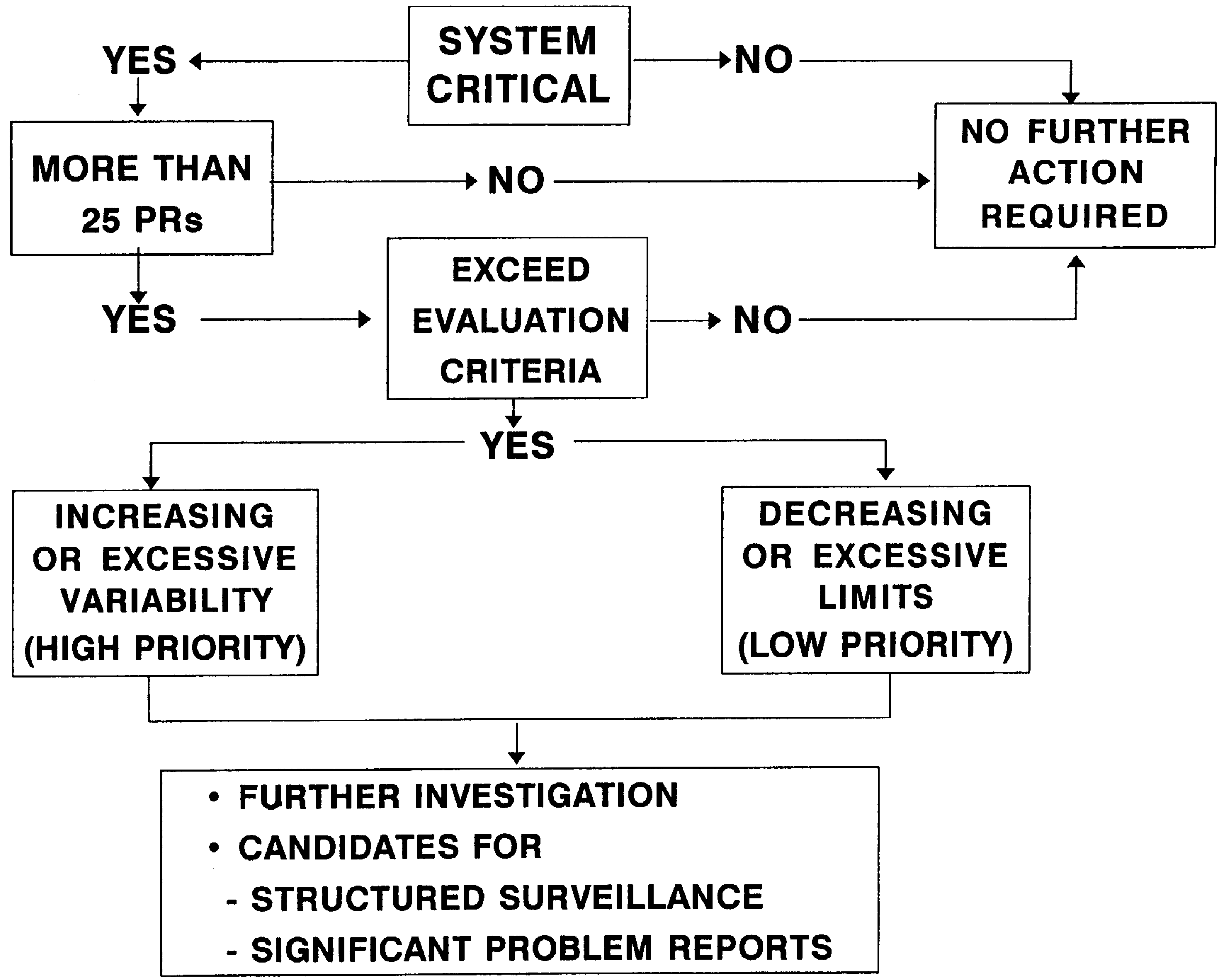
METHOD:
dBASE PROGRAM UTILIZING STATISTICAL ANALYSIS TECHNIQUES ON PRACA AND OTHER DATA SOURCES

BENEFITS:
- CONTINUOUS IMPROVEMENT OF SYSTEMS
- MORE EFFICIENT ALLOCATION OF RESOURCES

GSE TREND ANALYSIS DATA FLOW DIAGRAM



GSE TREND ANALYSIS REQUIREMENTS DECISION TREE



DOWNLOAD PRs FROM SPDMS2 PRACA SYSTEM 12/1/89 THROUGH 3/31/93	→ 22586 PRs 2680 UNIQUE SYSTEMS
TAKE 2680 SYSTEMS PULL OUT THOSE THAT ARE MARKED AS CRITICAL IN TR1287	→ 575 CRITICAL SYSTEMS
TAKE 575 CRITICAL SYSTEMS COUNT PRs FOR EACH SYSTEM IN GSE DATABASE PULL OUT SYSTMES WITH MORE THAN 25 PRs	→ 10218 PRs 120 SYSTEMS
TEST THESE 120 SYSTEMS AGAINST EVALUATION CRITERIA	→ 2836 PRs 42 SYSTEMS EXCEED EVALUATION CRITERIA
SEPARATE SYSTEMS THAT EXCEED EVALUATION CRITERIA INTO HIGH PRIORITY (INCREASING TRENDS OR EXCESSIVE VARIABILITY) AND LOW PRIORITY (DECREASING TRENDS)	→ 42 SYSTEM - 2836 PRs 9 HIGH PRIORITY SYSTEMS 497 PRs 32 LOW PRIORITY SYSTEMS 2339 PRs

LIMITS FOR MOVING AVERAGE CHART

Obs		PRs	
1	$\bar{x}_1$ (S_1)	P_1	
2		P_2	$\bar{x}_2$ (S_2)
3	$\bar{x}_3$ (S_3)	P_3	
4		P_4	$\bar{x}_4$ (S_4)
5		P_5	
6		P_6	
⋮		⋮	
25	$\bar{x}_{25}$ (S_{25})	P_{25}	
26		P_{26}	
27		P_{27}	

$$\bar{\bar{x}} = \frac{\bar{x}_1 + \bar{x}_2 + \bar{x}_3 + \dots + \bar{x}_{24} + \bar{x}_{25}}{25}$$

$$\bar{S} = \frac{S_1 + S_2 + S_3 + \dots + S_{24} + S_{25}}{25}$$

<u>Evaluation Limits</u>

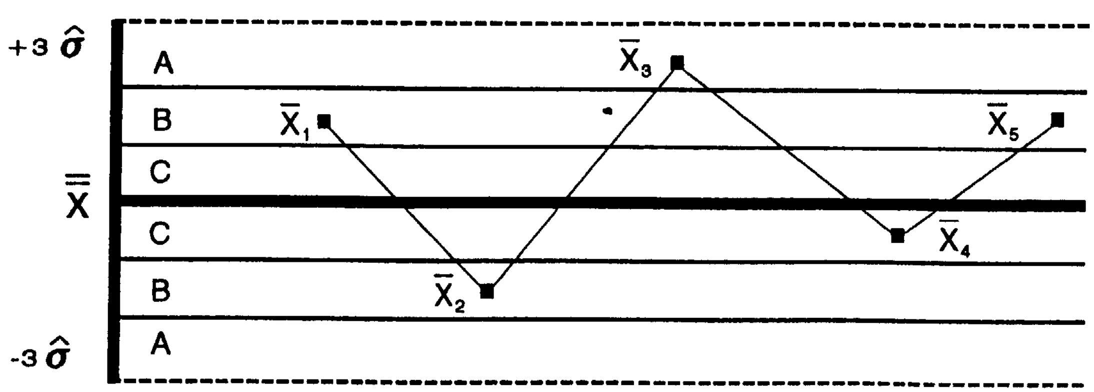
$$\text{Upper} = \bar{\bar{X}} + A_3 \bar{S}$$

$$\text{Lower} = \bar{\bar{X}} - A_3 \bar{S}$$

$$A_3 = \frac{3}{c_4 \sqrt{n}}$$

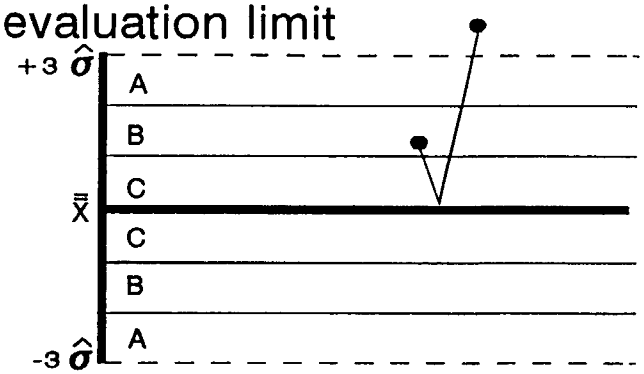
$$c_4 \approx \frac{4(n-1)}{4n-3}$$

n = Subgroup Size

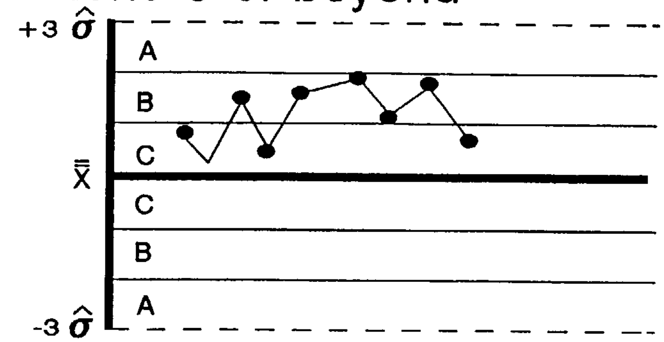


EVALUATION CRITERIA FOR INCREASING TRENDS

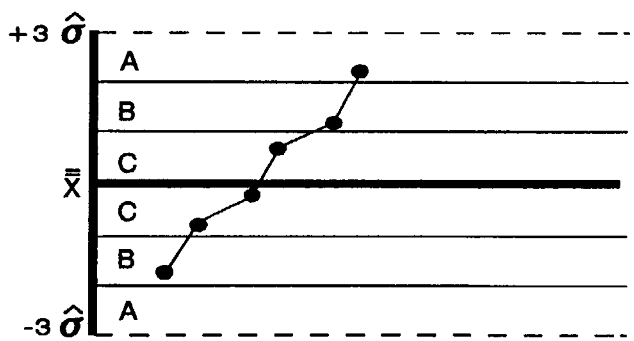
Test 1+ : One point beyond upper evaluation limit



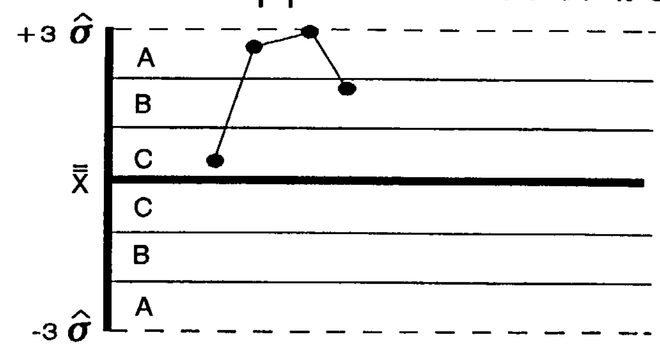
Test 2+ : Nine points in a row in upper Zone C or beyond



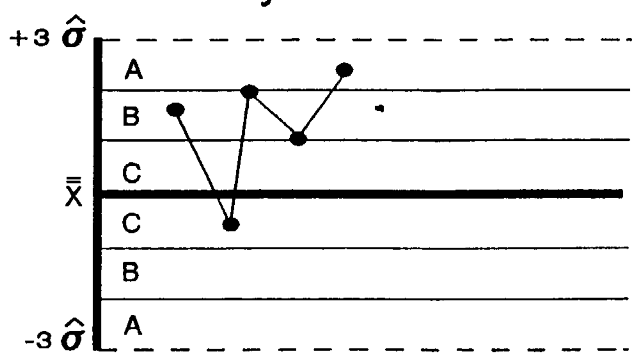
Test 3+ : Six points in a row steadily increasing



Test 5+ : 2 out of 3 points in a row in upper Zone A or beyond



Test 6+ : 4 out of 5 points in a row in upper Zone B or beyond



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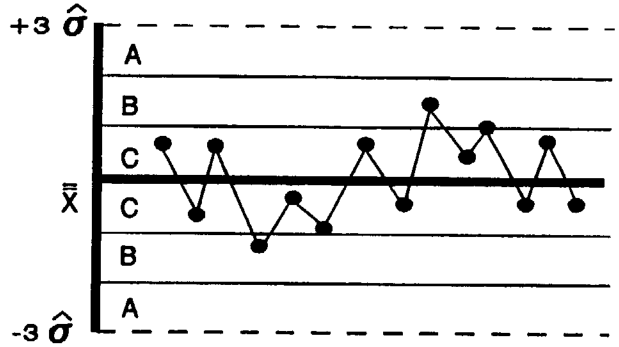
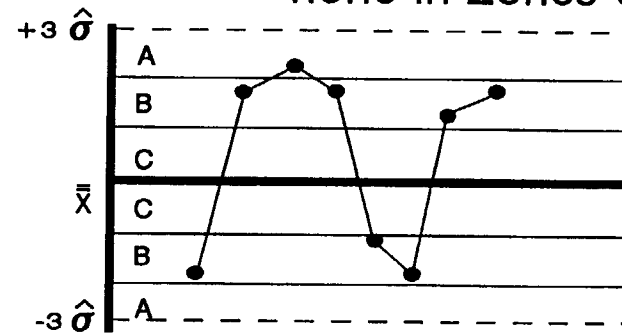
EVALUATION CRITERIA FOR EXCESSIVE VARIABILITY

Test 4 : Fourteen points in a row alternating up and down

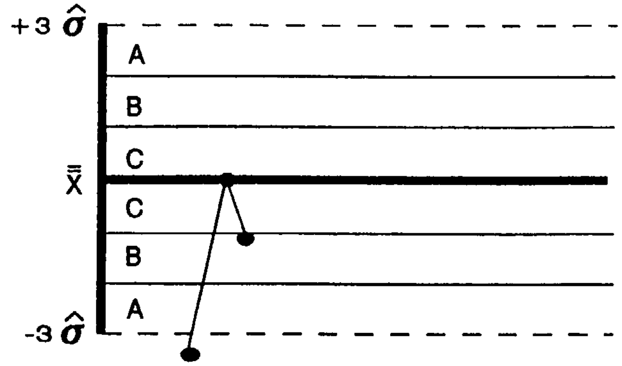


Test 8 : 8 points in a row on both sides of centerline with none in Zones C

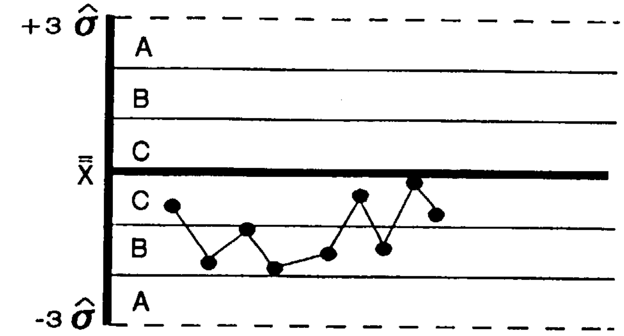


EVALUATION CRITERIA FOR DECREASING TRENDS OR EXCESSIVE LIMITS

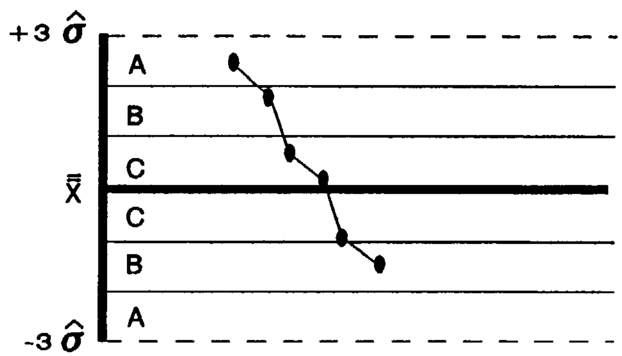
Test 1- : One point beyond lower evaluation limit



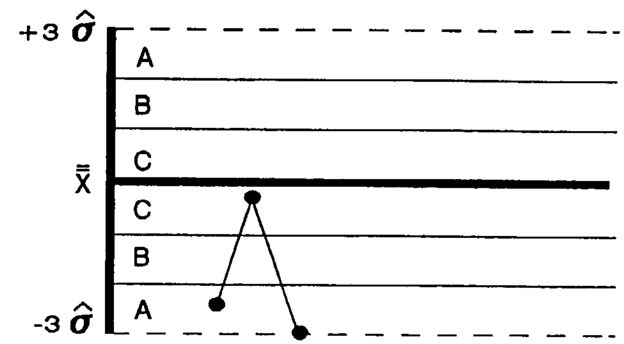
Test 2- : Nine points in a row in lower Zone C or beyond



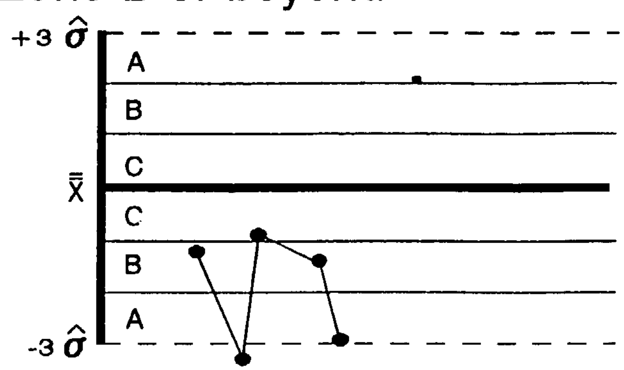
Test 3- : Six points in a row steadily decreasing



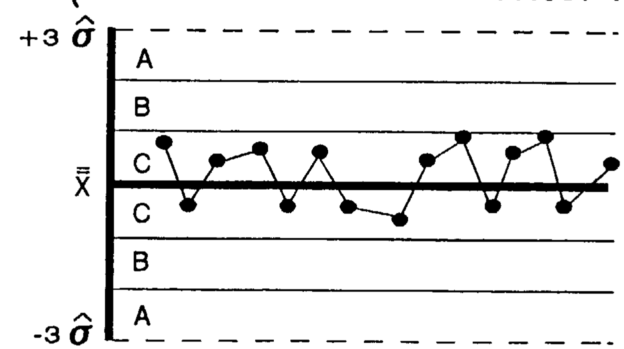
Test 5- : 2 out of 3 points in a row in lower Zone A or beyond



Test 6- : 4 out of 5 points in a row in lower Zone B or beyond



Test 7 : Fifteen points in a row in Zones C (above and below center line)



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SYSTEMS THAT EXCEED EVALUATION CRITERIA - INCREASING TRENDS OR EXCESSIVE VARIABILITY - 05/04/93

EICN	SYSTEM	# PRs	FAILED TESTS
A70-0668-00	PLATFORM, ORBITER MAIN ACCESS, OPF 1&2	108	1+ 5+
C77-0457-01	SYSTEM, LEAK TEST (SRM FIELD JOINTS)	85	5+
A70-0672-04	COVER SET, RCS ENGINE (ARCS)	57	5+ 6+
S72-0694-17	PANEL, GN2 ET ANTI-ICING	56	1+ 2+ 5+ 6+
U78-0103-00	ARM, ACCESS, ET INTERTANK	42	2+ 6+
S70-1204-00	UNIT, STATIONARY HYD PUMPING, ORB. OPF-3	40	5+
A72-1005-00	SYSTEM, MLP ENVIRONMENTAL CONTROL	40	2+ 5+ 6+
S70-0700-16	PANEL, FRCS OXID PRESS PURGE&QD ACT PNEU	37	2+ 5+ 6+
A70-0702-01	SET, HORZNTL INTRNL AFT FUSELAGE ACCESS	32	5+

TEST DEFINITIONS

1+ = ONE OR MORE POINTS ABOVE UPPER EVALUATION LIMIT
2+ = NINE POINTS IN A ROW ABOVE THE MEAN
3+ = SIX POINTS IN A ROW STEADILY INCREASING
4 = FOURTEEN POINTS IN A ROW ALTERNATING UP AND DOWN
5+ = TWO OUT OF THREE POINTS IN UPPER ZONE A OR BEYOND
6+ = FOUR OUT OF FIVE POINTS IN UPPER ZONE B OR BEYOND
8 = EIGHT POINTS IN A ROW ON BOTH SIDES OF CENTERLINE WITH NONE IN ZONES C

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EICN	SYSTEM	#PRs	FAILED TESTS
S70-0508-2R	UNIT, GROUND COOLANT (REFRIG. MODULE)	204	6-
A70-0702-00	SET, HORZNTL INTRNL AFT FUSELAGE ACCESS	196	2- 5- 6-
A72-0566-00	HDP, ORIGINAL & SMOOTH, SRB/MLP SUPPORT	182	2- 6-
S72-0813-00	SYSTEM, LO2, PAD MAIN PROP.STOR.&LOADING	166	2- 6-
A70-0519-00	PLATFORM, PAYLOAD BAY INTERNAL ACCESS	145	2-
C72-0810-00	POWER, DC GROUND, MLP	132	6-
A70-0698-03	SET, AFT/MID FUSELAGE VERT INTERNAL ACC.	117	2- 6-
S70-0700-07	COMPLEX, MMH FACILITY VALVE	105	6-
S70-0865-00	COMPLEX, HYPERGOL SAFING VALVE, OPF	98	2- 6-
A70-0668-03	PLATFORM, ORBITER MAIN ACCESS, OPF-3	93	2- 5- 6-
S78-0220-00	ASSEMBLY, ET INTERTK GND UMB CARRIER PLA	81	2- 6-
S77-1342-01	SRB JOINT HEATER UMBILICAL ELEC/MECH.	72	6-
U72-1317-00	TACAN	71	6-
H77-1227-01	HOIST, SRB HDP STUD TENSIONER, MLP	54	2- 7
S72-0809-00	SYSTEM, LO2, MLP ELECTRICAL	51	2-
S70-0815-04	PANEL, INTERFACE PIPING 2-3 TO VEHICLE	48	6-
S72-0685-01	GHE REDUCTION & BOTTLE FILL, PRIMARY	48	6-
S72-0685-05	PANEL, GHE ANTI-ICING, ORBITER	41	2-
H77-0838-00	CRANE, MOBILE, 60 TON GANTRY, SRB CASE	39	2- 6-
A70-0663-00	PLATFORM, ORBITER ENGINE SERVICE, MLP	37	2-
A70-0558-03	SET, VERTICAL INTERNAL ACCESS, CM	34	2- 6-
C72-0818-00	POWER, 400 HZ, MLP (FIXED)	33	2-
S70-0790-01	SET, QD/FILTER ASSY, (NH3 SERV)	33	6-
S72-0699-01	CONSOLE, GH2 T-0 SERVICING & CNTL, PAD A	32	2-
S70-0679-07	PANEL, GN2 PURGE SSME DRAG-ON	30	2- 6-
S70-1285-00	DOOR, PAD, PCR MAIN, POWERED	30	2- 6-
H77-0384-03	LIFTING BEAM, SRM 4-POINT (DUAL JACKING)	30	7
H70-0571-00	JACK, LANDING GEAR	29	6-
K61-1609-00	MANIPULATOR ARM, PCR TORQUE TUBE	29	2- 6-
C70-0870-01	SIMULATOR, HORIZ ZERO GRAVITY, PLBD RAD	28	2- 5- 6-
S70-0606-00	UNIT, LUBRICATION SERVICING, APU	28	2- 6-
S72-0694-01	PANEL, GN2 ET INTERTANK PURGE	28	6-
A70-0603-02	TOOL, RIGGING, ORB/ET FEEDLINE MATING	25	6-

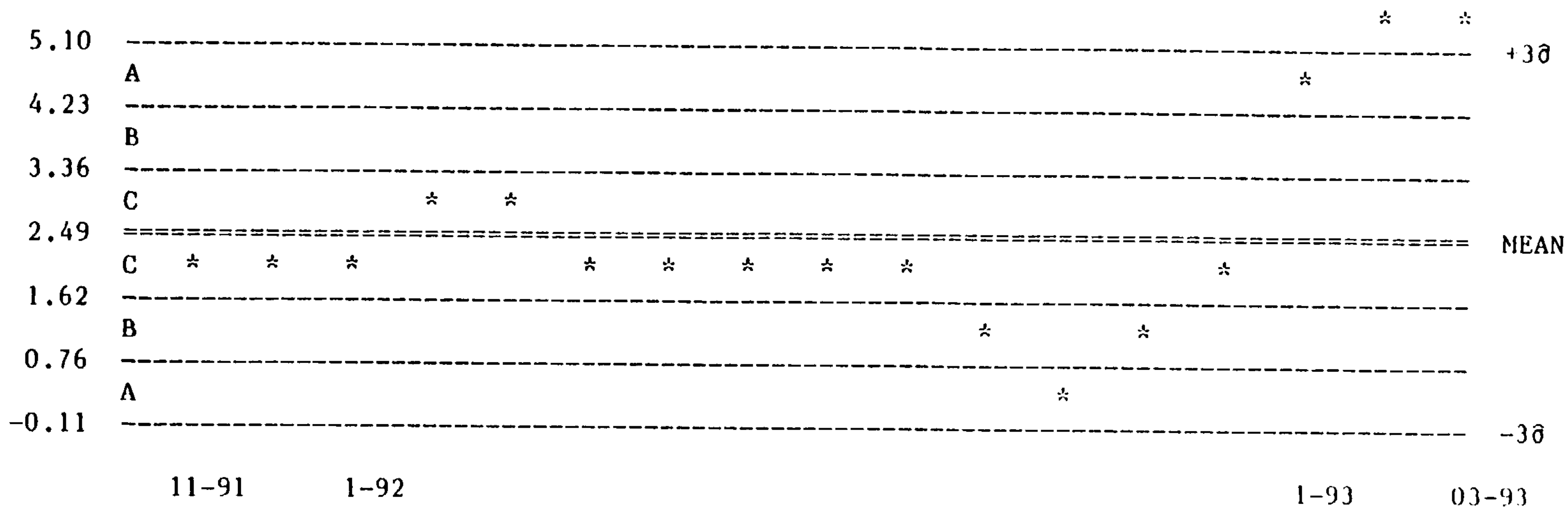
TEST DEFINITIONS

1- = ONE OR MORE POINTS BELOW LOWER EVALUATION LIMIT
2- = NINE POINTS IN A ROW BELOW THE MEAN
3- = SIX POINTS IN A ROW STEADILY DECREASING
5- = TWO OUT OF THREE POINTS IN LOWER ZONE A OR BEYOND
6- = FOUR OUT OF FIVE POINTS IN LOWER ZONE B OR BEYOND
7 = FIFTEEN POINTS IN A ROW IN ZONE C (UPPER OR LOWER)

LIMITS WERE CHANGED FOR THE FOLLOWING SYSTEMS THIS MONTH

EICN	SYSTEM	#PRs	FAILED TESTS
A70-0558-03	SET, VERTICAL INTERNAL ACCESS, CM	34	2- 6-
A70-0668-00	PLATFORM, ORBITER MAIN ACCESS, OPF 1&2	108	1+ 5+
A70-0702-00	SET, HORZNTL INTRNL AFT FUSELAGE ACCESS	196	2- 5- 6-
A70-0883-00	BRIDGE, P/L BAY AREA ACCESS, OPF-1&2	372	
A72-0566-00	HDP, ORIGINAL & SMOOTH, SRB/MLP SUPPORT	182	2- 6-
C72-0810-00	POWER, DC GROUND, MLP	132	6-
C72-0818-00	POWER, 400 HZ, MLP (FIXED)	33	2-
H70-0571-00	JACK, LANDING GEAR	29	6-
H77-1227-01	HOIST, SRB HDP STUD TENSIONER, MLP	54	2- 7
K61-1609-00	MANIPULATOR ARM, PCR TORQUE TUBE	29	2- 6-
S70-0679-07	PANEL, GN2 PURGE SSME DRAG-ON	30	2- 6-
S70-0865-00	COMPLEX, HYPERGOL SAFING VALVE, OPF	98	2- 6-
S72-0109-00	SYSTEM, MAIN PROPULSION LH2 LOADING, MLP	150	
S72-0694-17	PANEL, GN2 ET ANTI-ICING	56	1+ 2+ 5+ 6+
S72-0699-02	CONSOLE, GH2 FCSS SERVICING, PAD A	40	
S72-1107-01	PANEL, GN2 PURGE, SSME	35	
U72-1186-00	SYSTEM, VEHICLE HAZARDOUS GAS DETECTION	149	

SYSTEM: A70-0668 PLATFORM, ORBITER MAIN ACCESS, OPF 1&2
TOTAL PRS: 108 GRAND MEAN: 2.49
AVERAGE STANDARD DEVIATION: 1.34



POINTS PLOTTED ARE LISTED ON ATTACHED DATA SHEET

1+ = ONE OR MORE POINTS ABOVE UCL
5+ = TWO OUT OF THREE POINTS IN UPPER ZONE A OR BEYOND

DATA FILE A70-0668

GRP	PRS	AVG
91-11	1.00	1.67
91-12	2.00	2.00
92-01	4.00	2.33
92-02	4.00	3.33
92-03	1.00	3.00
92-04	2.00	2.33
92-05	2.00	1.67
92-06	3.00	2.33
92-07	1.00	2.00
92-08	1.00	1.67
92-09	1.00	1.00
92-10	0.00	0.67
92-11	2.00	1.00
92-12	3.00	1.67
93-01	8.00	4.33
93-02	6.00	5.67
93-03	3.00	5.67

PARETO ANALYSIS FOR A70-0668 - PLATFORM, ORBITER MAIN ACCESS, OPF 1&2 FROM 11/1992 TO 03/1993

TOTAL PRS: 27 OPEN PRS: 17

DETDUR	QTY	CAUSE CODE	QTY	WORK AREA	QTY
SURV	10	2	19	OPF-1	12
SURVE	5	4	2	OPF-2	10
A70-0	2	8	2	OPF-3	5
G45-5	1	T	2		0
INSP	1	A	1		0
INSPE	1	N	1		0
PLATF	1		0		0
V1091	1		0		0
V1264	1		0		0
V30-1	1		0		0
V3508	1		0		0

PART NO	QTY
79K06191	10
221-25-905	5
79K08118	5
79K16117	2
80K53604	2
79K08156	1
79K09851	1
80K53185	1
	0
	0
	0

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SYSTEM: C77-0457-01 SYSTEM, LEAK TEST (SRM FIELD JOINTS)
TOTAL PRS: 85 GRAND MEAN: 2.08
AVERAGE STANDARD DEVIATION: 1.48

```
 4.96 ------------------------------------------------------------------------------------- +3σ̂
      A                                                                               *    *
 4.00 -------------------------------------------------------------------------------------
      B                                                                          *
 3.04 -------------------------------------------------------------------------------------
      C                                      *                         *    *
 2.08 ===================================================================================== MEAN
      C   *                        *    *         *    *    *    *
 1.12 -------------------------------------------------------------------------------------
      B        *    *    *    *
 0.16 -------------------------------------------------------------------------------------
      A
-0.80 ------------------------------------------------------------------------------------- -3σ̂

        11-91      1-92                                                            1-93     03-93
```

POINTS PLOTTED ARE LISTED ON ATTACHED DATA SHEET

5+ = TWO OUT OF THREE POINTS IN UPPER ZONE A OR BEYOND

DATA FILE C77-0457-01

GRP	PRS	AVG
91-11	0.00	1.33
91-12	0.00	0.33
92-01	1.00	0.33
92-02	1.00	0.67
92-03	1.00	1.00
92-04	4.00	2.00
92-05	0.00	1.67
92-06	3.00	2.33
92-07	1.00	1.33
92-08	0.00	1.33
92-09	4.00	1.67
92-10	2.00	2.00
92-11	2.00	2.67
92-12	4.00	2.67
93-01	4.00	3.33
93-02	6.00	4.67
93-03	4.00	4.67

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PARETO ANALYSIS FOR C77-0457-01 - SYSTEM, LEAK TEST (SRM FIELD JOINTS) FROM 11/1992 TO 03/1993

TOTAL PRS: 20 OPEN PRS: 11

DETDUR	QTY	CAUSE CODE	QTY	WORK AREA	QTY
B5303	7	T	10	VAB	7
B5309	4	8	9	RPSF	4
SB-BI	3	2	1	VAB-3	4
VISUA	3		0	VAB SVAC1	2
C77-0	1		0	VAB SVAC3	2
TC-LS	1		0	VAB-1	1
VB624	1		0		0
	0		0		0
	0		0		0
	0		0		0
	0		0		0

PART NO	QTY
8U75902	8
8U75916	4
309-038	1
8U75916-100	1
8U76248	1
8U76502-01	1
8U76502-02	1
8U76502-03	1
8U76505	1
CD030336	1
	0

Goddard Abstract - Current Trend Analysis Activities

Goddard Trend Analysis Abstract for the workshop on the Automation of Time Series, Signatures, and Trend Analysis.

Walt Truszkowski, Troy Ames, Sid Bailin, Scott Henderson

Currently our group is evaluating mechanisms for automating aspects of the engineering telemetry trend analysis function now performed by spacecraft analysts. For the Extreme Ultraviolet Explorer (EUVE) spacecraft, this function is being supported by a system called the Generic Trend Analysis Workstation (GTAW). GTAW supports the computation of minima, maxima, averages, and standard deviations for specific data points over designated time periods, and can produce graphical plots of the results. Our group has been asked by the GTAW developers to explore extensions to their tool set that could autonomously identify noteworthy situations or trends within a data set and/or assist with the diagnosis and explanation of situations and trends. We began this task by breaking down the trend analysis function into sub-symbolic front end processing to support the identification of irregularities in the telemetry stream, and symbolic back end processing to support the interpretation of detected irregularitiesQin particular, to explain the irregularities, and then to predict future behavior from the explanation.

We have run some initial experiments using the TDAG algorithm as a sub-symbolic front end processor to identify surprising events. These experiments used simulated data sources and a crude scoring method to evaluate the algorithm's ability to form an accurate model of a data source, and to identify when that data source had been perturbed. Our initial results where supportive, and will be reported in this talk.

We ran up against three issues in the use of TDAG. The first is the translation of a real valued data stream with noise and missing data points into a stream of discrete symbols which can be processed by the algorithm. The second is scoring the predictive accuracy of the algorithm given the set of hypotheses in the algorithm's state queue and the actual next symbol seen. The third is setting the parameters of the algorithm so that a maximally accurate model can be grown within the constraints of available memory.

We are now running similar experiments on real telemetry data. Obtaining suitable data has been a difficult process because of the other demands on the time of the GTAW team. Anecdotes of this experience will be presented along with any real results available by the time of the presentation.

We are also in the process of adapting modeling tools which we had previously developed for simulation purposes to serve the role of back-end symbolic processing. The new tool will be used initially to track the state of the spacecraft based on the command stream which it has received. Statistical and sub-symbolic methods sacrifice some of their utility by averaging across different spacecraft states and activities. By exploiting information from the symbolic model about the state of a system we hope to produce analyses of the behavior of the spacecraft over time for specific activities. Examples could be the slew rate for an instrument, or the time required to fully charge a battery. This type of product requires the synthesis of low level information, such as the power usage of a subsystem, and high level information, such as the time at which charging began and the time at which full charge was achieved. While some of this high level information can be inferred from other telemetry points, the command history is an obvious secondary source and in some cases represents the true baseline against which behavior should be compared. We will present slides on the current prototype of this tool (DIG) and on its planned application to trend analysis.

We will briefly discuss our current plans for developing a library of models and the configuring of those models to support a trend analysis session. Additionally, we will discuss our plans for beginning work in providing a knowledge-based trend analysis capability for battery-related data.

NASA/GSFC Code 522.3 Trend Analysis Project

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Trend Analysis Project

Trend Analysis
NASA Code 522.3

Goal

Develop and deploy software that can autonomously identify anomalies and trends, and which can assist in the diagnosis and explanation of those anomalies and trends.

Institutional Vehicle

We have developed a relationship with the organization within GSFC responsible for FOT software, and hope to deploy our software within the context of a standard analysts workbench currently under development by that organization.

Initial Client

We have identified a sympathetic client within the Gamma Ray Observatory FOT who is himself an expert on the battery sub-system used in this and several existing and planned missions.

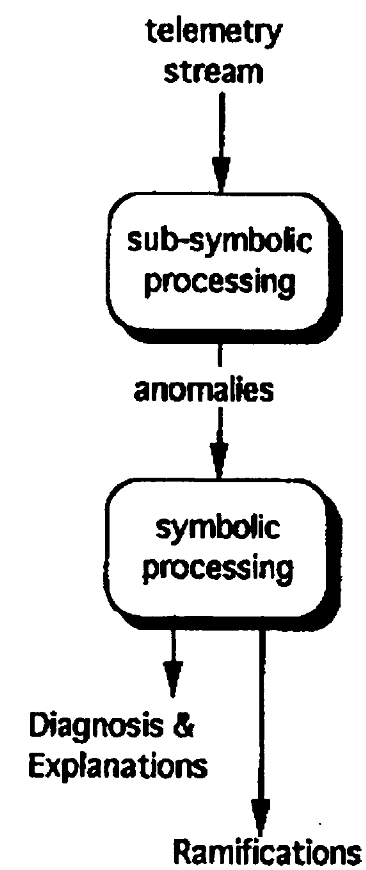
Approach

Sub-symbolic approaches

Application:	Characteristics:
• Learn patterns in a data stream • Use patterns to predict behavior • Report when data does not match expectations	• Lower up-front costs • Wide applicability • Higher through-put • No understanding

Symbolic approaches

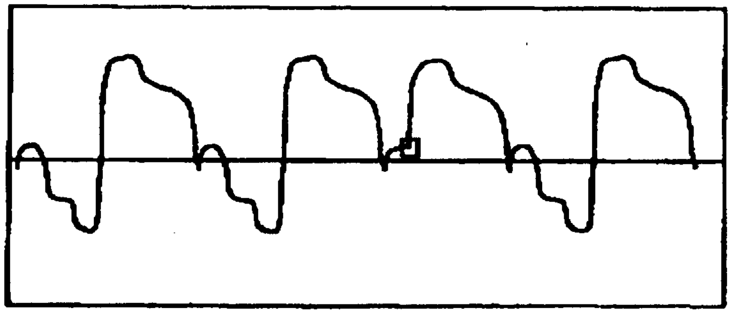
Application:	Characteristics
• Exploit operation constraints • Qualitative models of behavior • Associative rule bases • Bayesian Causal Modeling	• Higher up-front cost • Narrow applicability ability • Diagnosis & Explanation • Projection of ramifications



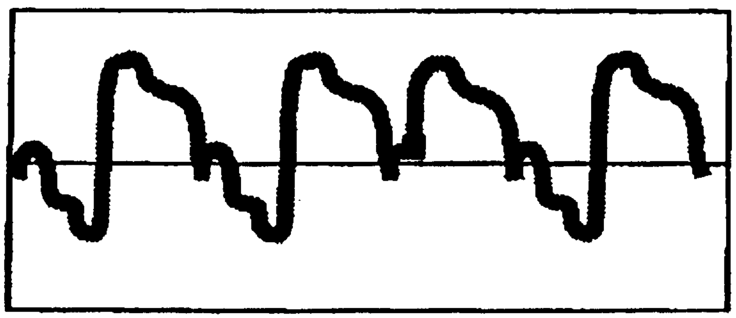
MO&DS Mission Operations and Data Systems 500

TDAG Experiments with synthetic data

Trend Analysis
NASA Code 522.3



Period = 100, no noise, no quantization.
Perturbed source inside of 15th cycle by skipping within the signiture.
Allowed TDAG a single guess.
By eighth cycle, TDAG guesses correctly 99% of the time.
Perturbation picked up on 15th cycle as drop in correct predictions.



Random noise of +/- 1.0 added to source range of 0...50
Perturbed source inside of 15th cycle.
Allowed TDAG 5 guesses.
TDAG never guesses correctly more than 55% of the time.
Perturbation not picked up.

Reduced noise to range of 0..1
TDAG predictions now in 90% range.
Perturbation picked up.

Patterns are learned quickly in noise free environments with consistent signatures.
Noise increases graph size and reduces accuracy, limiting ability to detect irregularities.

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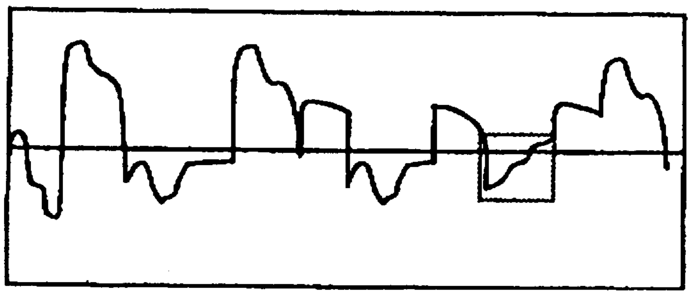
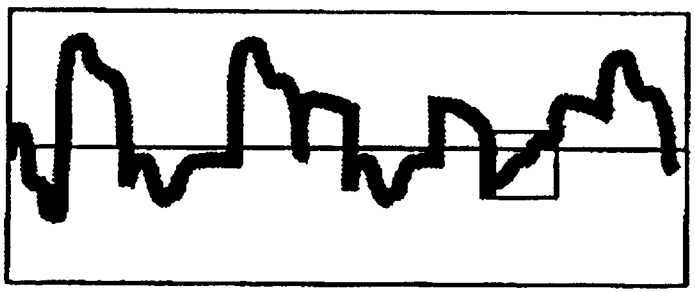
TDAG Experiments with synthetic data

Trend Analysis
NASA Code 522.3



Markov source with five contained sources, no noise, no quantization.
Perturbed source inside of 35th cycle (double training time)
by switching to new source.
Allowed TDAG 10 guesses.
TDAG performance is in the 90% range by the 14th cycle.
Perturbation picked up in the 35th cycle as drop in correct predictions.



Noise of 0..1 added to source range of 0...50
Perturbed source inside of 35th cycle (double training time).
Allowed TDAG 10 guesses.
TDAG performance is in the 60% range by the 20th cycle.
Perturbation seems to have been be picked up.

Pattern fragments can be learned for multi-mode data sources given longer training time.
Noise increases graph size and reduces accuracy, limiting ability to detect irregularities.

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TDAG Experiments with synthetic data

Trend Analysis
NASA Code 522.3

Early experience with raw telemetry values:

- Value range is much greater than in experiments.
- Have yet to find a data set with good regularity (i.e. a faithfully reproduced signature).
- Predictive accuracy is erratic
- Model hardens prematurely.

Strengths:

- Learning is unsupervised and does not require examples of anomalous data.
- The algorithm can accept a raw data stream since the period does not have to be known a-priori.

Weaknesses:

- Setting graph parameters to maximize the accuracy given the available resources is an art.
- Noise, irregularity, and missing values can disrupt the context used for accurate prediction.

Requirements for Symbolic Processing

Diagnosis of anomalies

Alternative approaches are associative rule-based systems and model-based reasoning.

Prediction of ramifications of a failure

May require functional/causal modeling of the spacecraft.

Presentation of results

Ideally presentation would be in terms of the spacecraft structure and the function of components within that structure.

Minimize the costs of building symbolic systems

We can exploit the fact that the small explorer series will use the same spacecraft bus and many subsystems from mission to mission.

This could be realized by borrowing the approach of Bernard Ziegler to the construction of hierarchical simulation models from libraries of component models.

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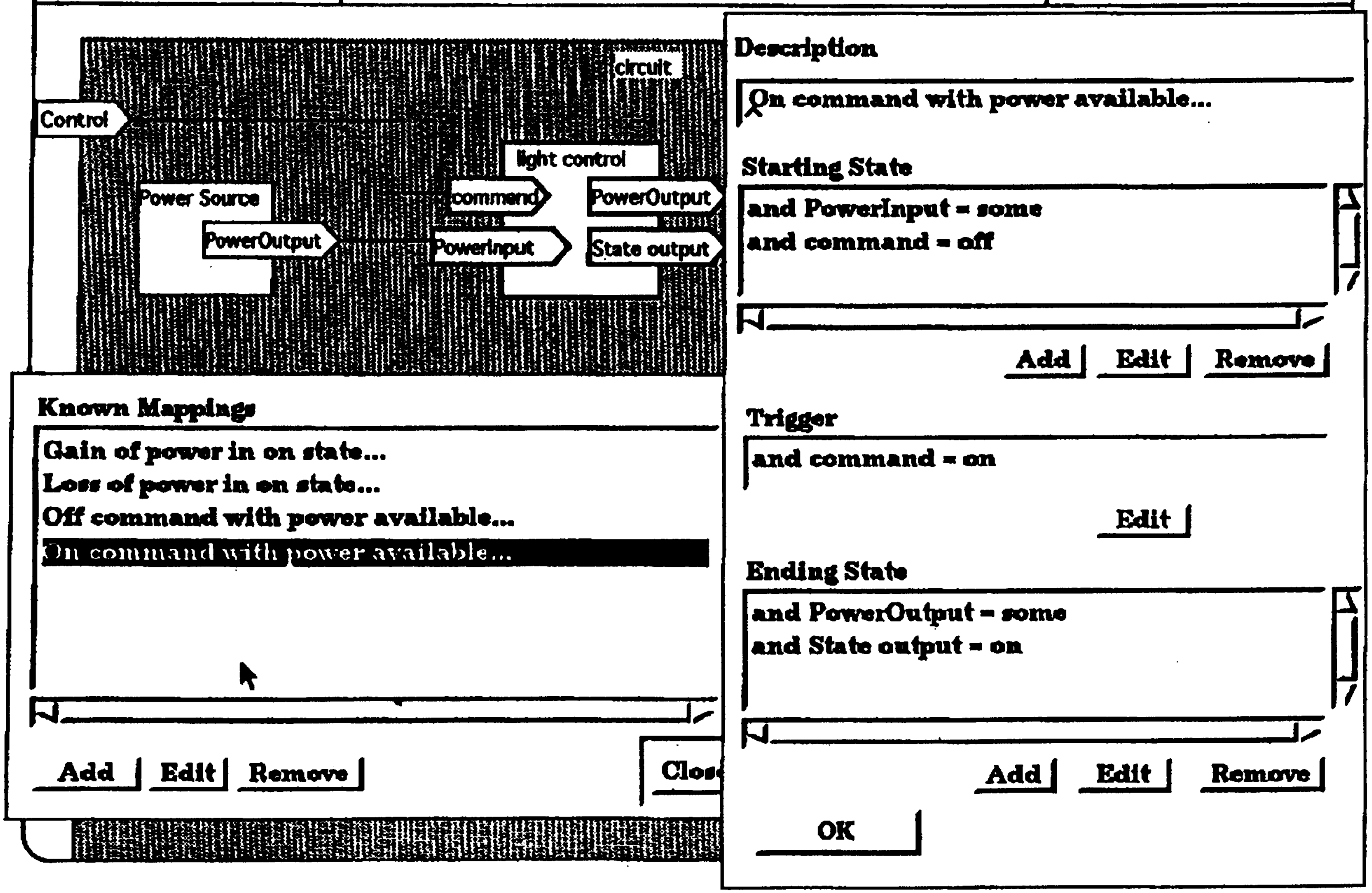
Construction of Model Libraries

Trend Analysis
NASA Code 522.3



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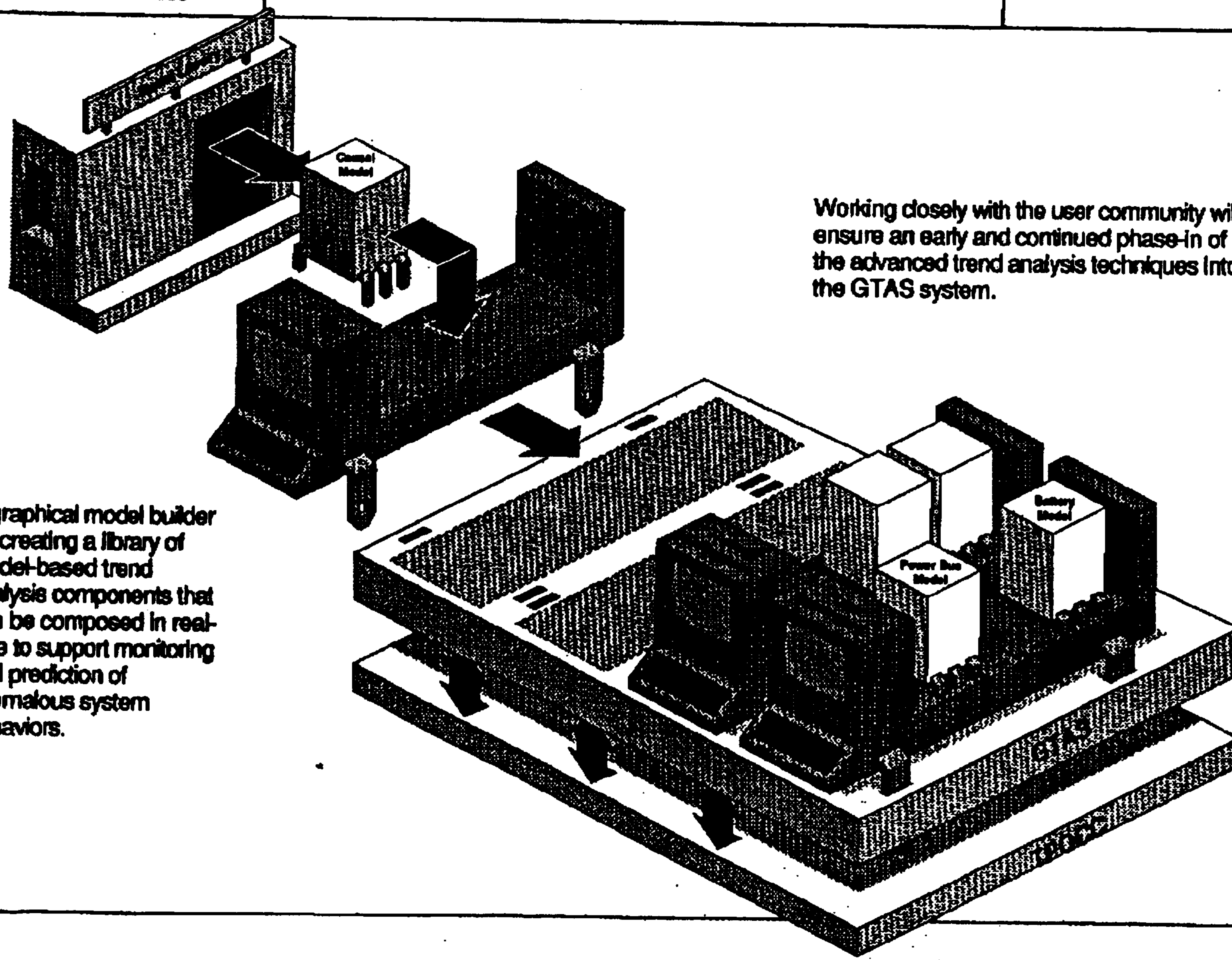
Model Use In Trend Analysis

Trend Analysis
NASA Code 522.3



Working closely with the user community will ensure an early and continued phase-in of the advanced trend analysis techniques into the GTAS system.

A graphical model builder for creating a library of model-based trend analysis components that can be composed in real-time to support monitoring and prediction of anomalous system behaviors.

Predictive Information Research for Aircraft Fault Management at NASA Langley

Anna Trujillo,
NASA LaRC

Predictive Information Research for Aircraft Fault Management at NASA Langley A widely held belief, by both pilots and researchers alike, is that providing predictive information on subsystem behavior to flight crews of commercial transport aircraft will be beneficial. For example, the ability to alert the flight crew that the engine will be out of oil in 20 minutes or that an engine seizure is imminent, may give them more options for dealing with the situation or at least help them be mentally prepared for it. There are data from incidents and accidents which suggest that these predictions are possible because there was evidence available on the flight deck of a failure well before any exceedences were reached. However, as with most new technologies that go onto modern flight decks, the benefits must outweigh the costs. The benefits of prediction could include: improved safety due to more strategic planning, earlier warnings so that more options (e.g., airports) are available, and increased crew situation awareness; and improved efficiency due to longer service time for aircraft components, fewer inflight shut-downs, and more fuel-efficient emergency procedures. The costs could include: developmental and production costs of prediction information; accuracy costs due to the risk of predicting the unknown future; and possible negative flight crew impact due to increased workload, confusion, or perhaps a degradation in situation awareness. It is the goal of this predictive information research program to attempt to quantify some of these costs and benefits and to provide recommendations in the form of information systems and displays that would be appropriate on the flight decks of commercial transport aircraft. The primary consequences regarding the implementation of predictive information in the flight deck pertain to its effects on the flight crew.

There are at least two options for implementing prediction information. The first is for the automation to make the prediction and to present it. The second is for the automation to preprocess certain key information elements and to allow the crew to use those elements to make a prediction. Whether the automation or the crew make predictions, the information for the predictions may (and probably should) be based on several key elements, which may include: current trends based on history, fault information, status information, and similar case histories. In the first option (automated), the automation might preprocess this information and then make a prediction based on these data. The system would then present that prediction to the crew. In the second option (aiding), the crew would only see the preprocessed information and would have to make the actual prediction themselves. Automating may be both faster and more accurate than having the flight crew process the information. But, some advantages of aiding are that the preprocessed information may be cheaper and more reliable, the crew may have information that the system may not have, and it may improve the crewis situation awareness.

A consideration of the strengths and weaknesses of both options, aiding and automating, must be taken into account to obtain a proper balance. Initial research in prediction at Langley has focused and will continue to focus on the utility or demand for predictive information. Human/machine experiments will explore variations of the two options stated above. In these experiments, the predictive information will be contrived rather than calculated. Factors such as accuracy, "look-ahead time," time until a critical event, and parameter type (e.g., oil pressure, generator voltage) will be manipulated. The goal is to discover a relationship between variations of predictive information (based on levels of aiding or automation and other factors) and the costs and benefits of that information.

For pragmatic reasons, research into the computational techniques for providing predictive information is being postponed. There are several computational obstacles that must be hurdled in order to provide predictive information, because only then can the assumption that predictive information increases the safety and economy of flight be fully substantiated. Some of these obstacles are the chaotic behavior of systems (especially failed systems), the poverty of data regarding system failures (neededfor development and testing), the variability in individual parameter behavior (conflicting with the desire for consistency in information provided for all parameters), and the computational and sensor limitations of current aircraft. In summary, our research objective for studying predictive information is to first determine the impact of predictive information on the man/machine system in terms of the safety and economy of flight. We will control and vary the omniscience of the predictive information, and we will explore the different levels of predictive information aiding, from aiding the flight crew to automating prediction, in order to enumerate its benefits. Since our objectives lie in the human/machine interaction aspects of predictive information, we welcome any assistance in research into the computational aspects of providing predictive information.

Predictive Information Research for Aircraft Fault Management at NASA Langley Research Center

Anna C. Trujillo Paul C. Schutte
NASA Langley Research Center
Hampton, VA

Outline

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1. Potential benefits
2. Issues
3. Research
4. Computational aspects

Potential Benefits of Predictive Information on the Flight Deck

Accident and incident cases suggest:

- Options were available to decrease severity of failure if there was foreknowledge
- Data was available to make prediction

Improved safety:

- Strategic planning
- Earlier warnings
- Increased situation awareness

Improved efficiency:

- Fewer inflight shut-downs
- Fuel-efficient procedures

Outline

1. Potential benefits
2. **Issues**
3. Research
4. Computational aspects

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Possible Costs of Predictive Information

- Developmental and production costs
- Accuracy costs of risk of predicting unknown future
  - Signal-Detection problem
- Possible negative flight crew impact
  - Workload
  - Confusion
  - Situation awareness degradation

Goal of Our Predictive Information Research

- Attempt to quantify costs and benefits
- Provide recommendations
  - Information systems
  - Displays for commercial transport aircraft

Options for Implementing Predictive Information

- Automated - Automation makes prediction and presents it
  - May be faster and more accurate
- Aiding - Automation preprocesses key information to allow crew to use information to make prediction

  May be:
  - Cheaper computationally
  - More reliable
  - Crew may have information that the system may not have
  - Increased situation awareness

Outline

1. Potential benefits
2. Issues
3. Research
4. Computational aspects

Current Research Objectives

- Focusing on utility or demand for predictive information
- Human/machine experiments explore:
  1. Automating and aiding levels
  2. Costs and benefits

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Current Research

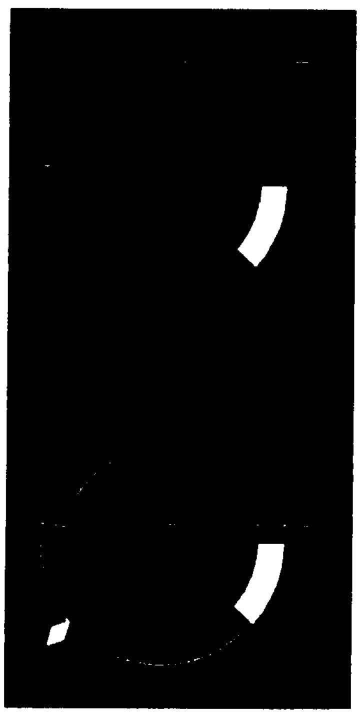
- **Predictive information contrived, not calculated**
  - Concerned with utility or demand of predictive information
  - Manipulated factors:
    - » Accuracy
    - » Look-ahead-time
    - » Time until critical event
    - » Parameter type

Experiments:

1. Long-term prediction with near-term predictors
2. Parameters pilots want or need predictive information on
3. Benefits of predictive information when dealing with faults

Long-Term Predictions of Time to Alert with Near-Term Predictors

- Pilots estimated the time to an alert
  - Viewed the dial for 5 or 10 seconds
- Alerts occurred 20 to 80 seconds later



- Standard Dial

- Predictive Dial
  - White ♦ shaped bug showed dial's value 5 seconds into the future
  - Perfect predictor

Results of Experiment

- Pilots overwhelmingly preferred dials with predictive information
  - Higher confidence and less effort
  - Liked predictive dial because:
    - » Gave advance warning to alert
    - » Use it to keep value out of alert range
- Standard dial had least absolute difference between subject's estimate and actual time to alert

Pilots preferred the near-term predictive information dial but objective data does not support its use for long-term prediction

Selecting Parameters with High Payoff from Predictive Information

- Pilots will order cards containing parameters that may benefit from predictive information
- Begin to determine where predictive information may be most beneficial

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Benefits of Predictive Information In Dealing with Faults

- In a simulator, observe how pilots use predictive information in handling an impending alert
- Determine:
  1. How predictive information increases the safety and economy of flight
  2. Pilot preferences for look-ahead time $\rightarrow$ vary prediction time from 30 seconds to 20 minutes
- Perfect predictor

Long-Term Objectives

- Determine where pilots want or need predictive information
- Design displays

  Based on:
  - Ability to predict parameter behavior
  - Pilot preferences

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Outline

1. Potential benefits
2. Issues
3. Research
4. Computational aspects

Computational Basis for Predictive Information

- Current trends based on history
- Fault information
- Status information
- Similar case histories

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Computational Obstacles of Predictive Information

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- Chaotic behavior of systems
- Poverty of data regarding system failures
- Variability of parameter behavior
- Computational and sensor limitations on aircraft

Summary

- We will determine impact of predictive information

  Control:
  - Predictive information
  - Level of information aiding
- If predictive information proves beneficial, then we will pursue research into the computation of that information

Summary of the Afternoon Discussion Session
Padhraic Smyth, Chair

(edited by Phil Laird)

P.S: To seed the discussion, I've listed several dimensions along which to analyze time series:

- Purpose: causal models vs. prediction vs. anomaly detection.
- Operations: manual vs. semi-automated tools vs. full automation.
- Data vs. prior knowledge: data manipulation alone only goes so far; prior knowledge is essential to gofarther.
- Transients vs. long-term dynamics. Temporal properties are more important in the former than in the latter, which sometimes may be treated as "static."
- Representation: signal amplitutde, thresholds, AR/MA models, wavelets, linear models, transform methods, non-linear methods, Markov models, etc.
- Noise vs structure: which is which?
- Raw data vs annotated data (unsupervised vs. supervised)

Also, we should ask what the hard problems are. Some that have been discussed here are:

- Matching problem/data to model/algorithm.
- Feature extraction, data preprocessing (a "black art").
- Combining data and prior knowledge.
- Is "normal behavior" quantifiable?

NS: Is there a taxonomy of datasets, a small set of characteristic parameters? Andreas' dataset attributes slide seemed to provide some ideas for that.

RS: Dimension reduction is hard, but at least it makes the problem solvable. The key problem is to find better ways to reduce the dimension.

PL: Is there a fundamental measure of dimensionality, as there is for pattern classification?

AW: Sometimes low dimensionality is bad: higher dimensionality can make it easier. For example, ANNs often use a large number of dimensions/parameters, because embedding the problem in higher dimensional space makes it easier to represent. Also, you need to be careful about the term "degrees of freedom" (various meanings exist).

PS: Is a nonlinear approach really necessary? In light of Wold's Theorem, aren't linear models sufficient?

TM: A simple counterexample: train a net to pick points that lie within the inner of two concentric circles. The decision surface is nonlinear, yet a network learns it after seeing examples involving only one point outside the inner circle.

RS: Networks do provide some protection from overfitting, through the relationships among the parameters, but it is possible to overtrain. They are also good for spotting outliers (errors) in the training data. Conventional statistics don't have this property.

PS: Nonparameteric statistical methods are better at this than parametric statistics.

AW: What really is a *linear* time series? Here's a test: given a timeseries, take the Fourier transform, randomize the phase, and reinvert. The resulting signal has the identical power spectrum, but all effects due to nonlinearities are destroyed. If you then get same "answer" from your timeseries analysis box, the box is a linear method measuring linear structure.

JN: That test is also a good test for chaos. If you get the same dimension, then the data wasn't chaotic.

PS: What are the hard problems at some of the other centers?

DH: Some are just a matter of software and data handling. Also, it's often hard selling new techniques to customers: showing that they work, explaining how they work.

CM: People in charge of operations just won't tolerate "black boxes," things they don't understand and in which they have no confidence.

PL: Can we combine these problems into operations areas by bridging, combining techniques from different disciplines? There is then less of a perception that the technique arises in a field that the user doesn't understand.

JZ: Code D from HQ, and the JSC Software Technology Branch are trying to build toolkits for this purpose, especially for the OHMS/RCS (Orbital Health Management System/Reaction Control System). This is just now getting underway.

PS: There are many good opportunities here for university collaborations.

CM: The University of Cincinnati has a group studying radial basis nets, and got data from LeRC for the purpose.

Unknown: NASA seems reluctant right now to give out data and software.

RS: Data is actually more valuable than software, but software is perceived as having value by NASA and hence its distribution is more restricted.

CM: Datasets need to be carefully documented and maintained.

SC: I worry somewhat about the "toolkit" idea, and would encourage adopting a broader view. Tools change and evolve. Also, feature extraction is crucial. E.g. the problem of sensitivity to the particular test probably can be handled with appropriately chosen features.

RS: Things are not now ready for off-the-shelf tools, but may well be in a few years. In our project, we modularized the system so that different tools could be plugged into the various boxes.

WI: The intention of toolkits is not to freeze research; all the tools in the toolkit are useful for a variety of jobs. The general problem is getting the system used; and a toolkit facilitiates that screening process.

PL: There is a big gap between knowledge intensive methods and other methods in that there seem to be no systematic ways to incorporate knowledge. Yet that seems essential to the toolkit notion.

JN: How do we handle data that doesn't come evently spaced or is otherwise hard to "deconvolve"?

RS: Humans always "cheat"–use side information not given in the formal problem.

PS: And in some applications that really makes the difference between what a machine can and cannot do.

SC: There is hope that recurrent neural nets will solve some of these problems.

TM: I have worked with ANNs in oil and medical industries. There the technique was to put the signal *attributes* rather than the signal itself into the network.

AW: I am surprised that no one has brought up *robust* timeseries estimation. I expected more discussion of how people spot outliers and what they do with them. Outliers arise, e.g, from errors in the data. Are there any general approaches?

SC: You can't separate outliers from knowledge of the domain.

JZ: When something abnormal happens, you can look for clues in the other things happening at about the same time. For this to work, though, you need enough system-wide information.

PS: Astronomers seem to have have a different philosphy from engineers about modeling data.

WI: How can you quantify the quality of your data, or the quality of the expert giving you the training data? Who's driving whom when the expert and the end user are largely the same?

RS: I would propose looking, not for major applications, but small applications with positive value and high likelihood of success.

NASA Workshop on the Automation of Time Series, Signatures, and Trend Analysis
May 12, 1993

Abstract: The Planetary Passage Prediction Project

Silvano Colombano and Nick Groleau
Artificial Intelligence Research Branch
NASA Ames Research Center

We have recently started an effort aimed at discovering distant planetary systems from the observation of light fluctuations of their central star. The project is called Planetary Passage Prediction Project, or PPPP, or P4 for short. The idea is to build a predictor for the emitted light time series and recognize significant deviations of the data as planet phenomena. In a first effort, we will focus on ACRIM (Active Cavity Radiometer Irradiance Monitor) data obtained from the SMM (Solar Maximum Mission) satellite in 1989.

We envision making use of the cascade-correlation artificial neural network algorithm to build and train the predictor network. The input data requires a time delay line from the time series. The output is a single predicted data point. Cascade-correlation is a technique that provides for the automatic generation of hidden units in multiple layers arranged in a cascade of connections.

More advanced work will include attempts at modifying the algorithm to accomodate on-line learning and automatic determination of the number of input units and their relative time delay. We are working closely with the FRESIP project which is trying to secure funds to build a satellite telescope for planet discovery.

Nonlinear Regression in Time Series for Short Term Prediction

Richard Kraft
Ames Research Center

Following the work of Ruelle, Collette, Eckmann, and others, techniques are available to make predictions in the short term for time series associated with deterministic chaotic systems. Although no universally accepted definition of "chaotic system" exists, there is widespread agreement that a necessary condition is the existence of a positive Lyapunov exponent for the system, which essentially indicates that there is extreme sensitivity to a set of initial conditions of full measure.

This technique posits the existence of an attractor in a phase space of time delays. The attractor is usually fractal in nature. There is mounting evidence that the dimension of the attractor is closely related to the expected predictive accuracy.

Of central importance is the ability to accurately estimate hundreds or thousands of parameters specifying the attractor in a tractable manner. Current research is being devoted to this problem and its effective application in the above context. Another focus of research concerns combining stochastic modeling with nonlinear deterministic modeling, as many systems exhibit a range of behaviors. Techniques are being developed to identify the mode of behavior and to regulate the forecasting technique accordingly.

Grammar Induction as a Mechanism for Sequence Analysis

Kevin Thompson
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April 9, 1993

The task of "supervised learning" has dominated research in empirical machine learning for many years. Supervised learning systems acquire rules from training examples labeled with a special *class* attribute. These learned rules, or concepts, can then be used to *classify* test instances.

A major limitation of most systems for supervised learning is their focus on fixed attribute-value languages; very few systems are able to learn from structured data, or data with differing numbers of attributes. One obvious approach to learning from *sequential* data is to learn formal grammars. Context-free grammars (CFGs) have the potential of being more expressive than Markovian models, which are essentially probabilistic versions of the less-powerful class of regular expression languages or finite-state machines. Grammar induction is typically applied to sequential domains – e.g. ones with consecutive states, but in which the temporal aspect *per se* is not an issue, like natural languages or amino acid sequences. However, we believe that grammar induction may be appropriate for certain types of signature analysis; CFGs have the potential both of giving better predictive accuracy because of their added expressiveness, and of leading to more understandable rules, because CFGs are often more succinct than their finite-state machine counterparts.

We have recently begun work on inducing simple context-free grammars from examples. We are exploring three key issues. Because of the enormous number of possible grammars from a given set of sentences, effective induction requires strong constraints on the space of grammars; we are thus exploring structural constraints on instances. We are investigating better evaluation functions; earlier work typically evaluates grammars based on either their size (simplicity) or their ability to parse sentences, but little work uses both in any coherent way. An evaluation function based on the minimum description length (MDL) principle should give better guidance in search for the best grammar. Lastly, we are experimenting with probabilistic versions of context-free grammars, as "all-or-none" rules have limited applicability in many natural domains.

Dynamic System Monitoring using Pattern Recognition and Hidden Markov models

Padhraic Smyth
JPL

Conventional fault detection and diagnosis techniques rely on relatively exact models of the system being monitored being available. In practice it is not unusual that there is no accurate system model available a priori due to the fact that the real system is complex and non-linear. Examples of such systems are the large 70m and 34m ground antennas in the Deep Space Network (DSN)(designed and operated by JPL for NASA). There is significant interest in both maintaining the reliability of these antennas as they become older and in improving their performance as deep space communication moves to higher frequencies (from S,X-band to Ka-band) and longer duration planetary missions become common.

In this talk I describe recent work at JPL on developing adaptive methods for online monitoring of DSN antenna pointing systems. The methods rely on the use of time series models, pattern recognition, and Hidden Markov models. Standard autoregressive (AR) time series models are fit to the sensor data in real-time. Changes in the values of the AR coefficients are then detected by a pattern recognition component which generates posterior probabilities that the system is in a particular state given the data observed in that window. Finally, a hidden Markov model (HMM) is used to integrate the state probabilities over time, thus providing temporal context.

The pattern recognition model is trained in advance using available system data and the HMM component is specified based on prior knowledge of system failure rates. Field tests to date indicate that the overall model has both rapid detection capabilities and excellent resistance to false alarms. Ongoing work involves the use of density estimation methods to detect novel states which have not been predicted in advance, and the use of Bayesian methods to adapt both the parameters and the structure of the overall model in real-time. The model is generally applicable to monitoring of any dynamic system where no accurate system model is known, but where training data from the system is available a priori.